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ENHANCING THE GASOLINE VEHICLES' CO_2 EMISSIONS ESTIMATION IN MONTREAL

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présentée par : NOURI Pegah

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RÉSUMÉ

Les changements climatiques sont devenus l'un des enjeux environnementaux principaux des dernières années, les émissions de gaz à effet de serre (GES) étant pointées du doigt comme principal coupable. Globalement, les décideurs des politiques tentent depuis un certain temps de réduire les émissions des GES à travers diverses mesures et politiques. Considérant qu'en Amérique du Nord, le domaine du transport compte pour 30% des émissions totales, il est devenu le centre d'attention pour les initiatives de réduction des émissions de GES.

La première étape à suivre pour implémenter une politique ou une stratégie nouvelle est d'estimer son impact potentiel sur les émissions de GES ; à cette fin, l'utilisation des modèles d'émissions est essentielle. Depuis les années 70, plusieurs chercheurs ont développé des modèles d'émissions variés, atteignant une apogée lors des années 80. Les modèles d'émissions ont évolué depuis à travers plusieurs mises à jour, mais il y a encore de la place à l'amélioration. Puisque ces modèles sont extrêmement sensibles aux variations des données utilisées et aux méthodes de calibration, ne pas utiliser des bases de données précises ou effectuer une calibration fautive peut provoquer des estimations erronées.

Gardant cela en perspective, l'objectif principal de cette recherché est de contribuer à l'amélioration des modèles d'estimation des émissions. Pour se faire, trois objectifs ont été identifiés : le premier objectif spécifique est de fournir une revue des modèles disponibles et d'évaluer l'impact des divers facteurs sur les émissions. Le deuxième objectif spécifique est de comprendre et d'évaluer le modèle principal d'évaluation d'émission au Québec et d'identifier les variables qui sont les plus sensibles et qui peuvent le plus affecter les estimations. Le dernier objectif spécifique est d'améliorer la méthodologie pour développer les cycles de conduite utilisés dans les modèles d'émissions.

Afin d'atteindre ces objectifs, nous dédions le premier chapitre à discuter du sujet des changements climatiques et du domaine des transports en détail, avant d'aborder une introduction aux stratégies et politiques principales visant à réduire les émissions provenant du transport. Dans le deuxième chapitre, une revue détaillée des études disponibles sur le calcul, l'estimation et la représentation des émissions est fournie. Dans ce chapitre, le concept des cycles de conduite est également discuté, un facteur qui a été le centre d'attention dans les analyses d'émissions en raison de son impact significatif sur les émissions et de sa complexité de représentation.

Pour parvenir à nos objectifs, divers ensembles de données étaient nécessaires à l'analyse. Quelques-uns étaient déjà disponibles ; par contre, l'ensemble de données principal à cette étude, les données liées à l'utilisation du véhicule, a dû être collecté. Tous les ensembles de données et le processus de collection des données sont décrits dans le chapitre 3.

Pour le premier objectif spécifique, basé sur les modèles d'émissions qui sont présents dans la revue littéraire, une analyse de la sensibilité des facteurs est menée dans le quatrième chapitre. Cette analyse cherche à démontrer l'impact des facteurs principaux sur les émissions véhiculaires ainsi qu'à identifier les obstacles et omissions des modèles courants. Les résultats démontrent que la capacité du moteur des véhicules est le facteur le plus sensible ; une variation de 10% de la capacité moteur, soit l'équivalent de 0,5 litre, peut augmenter la consommation totale de carburant de 25%. D'autres aspects ayant un impact important sont, en ordre décroissant, la température, la vitesse ainsi que le poids du véhicule. Les résultats démontrent toute l'importance d'avoir des données précises dans le processus d'estimation des émissions. Dans une analyse croisée, considérant tous les facteurs, les meilleurs et pires scénarios sont évalués. Sur la base des résultats obtenus, en comparant les conditions les plus favorables et les moins favorables à la consommation de carburant, on constate que cette consommation peut s'avérer jusqu'à 13 fois plus élevée : une valeur fulgurante qui confirme comment l'amélioration et la dégradation de divers facteurs peuvent contribuer à la consommation de carburant.

Dans le cas du deuxième objectif spécifique, le modèle principalement utilisé en Amérique du Nord (MOVES) est introduit en démontrant de quelle façon les ensembles de données peuvent affecter les émissions calculées par le modèle. MOVES est un modèle très efficace, toutefois il est complexe et sensible ; la complexité et la sensibilité du modèle le rendent plus enclin aux erreurs d'estimations. Souvent, les décideurs et même les chercheurs utilisent le modèle sans être conscients des erreurs possibles. Dans le chapitre 5, l'impact des différentes variables sur les estimations d'émissions est démontré.

L'un des éléments principaux de MOVES (et des modèles d'émissions les plus récents) est le cycle de conduite, qui représente le schéma de conduite moyen. La précision de l'estimation d'émissions dépend fortement de la précision des cycles de conduite utilisés ; l'utilisation de cycles de conduites ne représentant pas les schémas de conduite réels peuvent donner des résultats erronés.

Comme objectif principal de cette recherche, nous visons à contribuer à l'amélioration de la méthodologie des cycles de conduite afin d'offrir un cycle de conduite plus représentatif et précis. Le chapitre 6 fournit les détails de cette méthodologie. Bien que la méthodologie des cycles de conduite ait plusieurs étapes, l'une d'entre elles est de diviser les profils de vitesse en plus petites sections, appelées microtrips. Il y a plusieurs méthodes pour établir les paramètres sous lesquels ces microtrips sont créés; dans cette étude, ces méthodes, ainsi que celles basées sur la distance, sont comparées afin de déterminer lesquelles offrent les cycles de conduite les plus exacts. Les résultats montrent que les microtrips basés sur les caractéristiques spatiales produisent des cycles de conduite plus représentatifs et que, parmi les diverses caractéristiques spatiales, celles fondées sur la distance sont les plus justes.

Dans le chapitre final, Chapitre 7, une revue des découvertes principales de la recherche est fournie. De plus, considérant que certaines limites et obstacles ont été présents lors de cette recherche, nous les discutons brièvement. Le processus d'estimation des émissions est un travail non achevé, et malgré qu'il ait évolué depuis les dernières décennies, il y a encore de la place à l'améliorer et à repousser notre compréhension et nos outils d'analyse plus loin. Dans la dernière section, des recommandations pour les études futures sont proposées afin de s’approcher de ce but.

ABSTRACT

Climate change has become one of the most critical environmental concerns of the past decades, with greenhouse gas (GHG) emissions being identified as the main culprit. Globally, policy makers have been trying to reduce GHG emissions through various policies and strategies; given that in North America, transportation accounts for 30% of the total emissions, it has become the focus of attention for GHG reduction initiatives. The first step to implementing a policy or strategy is to estimate its potential impact on emissions; the use of emission models is necessary to assess the potential impact of those initiatives. Since the 70s, many researchers have developed different models, reaching a peak in the number of studies in the 80s. The emission models have evolved since then and have been regularly updated, but still need improvements. Since these models are extremely sensitive to their input datasets and their methods of calibration, failing to provide accurate input datasets or calibration can result in erroneous estimations.

Keeping that in perspective, the main objective of this research is to contribute to the improvement of emission estimation models. To do so, three specific objectives were identified: the first specific objective is to provide a review of the available models and evaluate the impact of different factors on emissions. The second specific objective is to understand and assess the main emission model that is used in Quebec and identify the variables that have the highest level of sensitivity and can most affect the estimates. The last specific objective is to improve the methodology for developing driving patterns used in emission models.

To achieve our specific objectives, we dedicate the first chapter to discussing the subject of climate change and transportation in details as well as bringing forth an introduction to the main strategies and policies to reduce the emissions from transportation. In the second chapter, a comprehensive review of the available studies on emissions measurement, modeling and estimation packages are provided. In this chapter, the concept of driving pattern is also discussed, a factor that has been the focus of attention in emissions analysis due to its significant impact on emissions and its complexity of representation.

To fulfill our objectives, different datasets were required for our analysis. Some of the datasets were already available; however, the main dataset that was essential for this study, namely the vehicle activity data, required data collection. All of the datasets and the process of the data collection are demonstrated in Chapter 3.

To achieve our first specific objective, and based on the emission models that were presented in the literature review, a sensitivity analysis is conducted through Chapter 4. This analysis is aimed to demonstrate the impact of the main factors on vehicle emissions as well as to identify the challenges and gaps in the available models. The results showed that vehicles' engine capacity is the most sensitive factor; a 10% change in engine capacity, being equal to 0.5 L, can increase the total fuel consumption by 25%. Other components factoring heavily are, in descending order, the temperature, speed and the vehicle's weight. The findings highlight just how important it is to have precise data for emission estimations. Also in a cross analysis, considering all the factors, a best and a worst-case scenario are evaluated. Based on the results, comparing the most fuel-efficient conditions with the least fuel-efficient conditions, the consumption can increase by up to 13 times: a staggering figure that confirms how improvements or deterioration of multiple factors can contribute to fuel consumption.

In our second specific objective, the main emission model in North America (MOVES) is introduced by demonstrating how the input datasets can affect the emissions calculated by the model. MOVES is a very capable, yet complex and sensitive model; the sensitivity and complexity of the model make it prone to errors of estimations. Often, policy makers or even researchers use the model without being aware of the possible errors. In Chapter 5, the impact of different variables on emission estimations is demonstrated. One of the main components of MOVES (and most of the recent emission models) is the driving cycles, which represent the average driving pattern. The accuracy of the emission estimation strongly depends on the accuracy of the driving cycles used; using driving cycles that do not represent real-world driving patterns could provide erroneous results.

As the main objective of this research, we seek to contribute to the improvement of the driving cycle methodology in order to provide a more representative driving cycle. Chapter 6 provides the details of the methodology. While driving cycle development has different steps, one of them is to divide the speed profiles into smaller sections, called microtrips. There are several methods for establishing the parameters of the microtrips created; in this study, these methods, as well as a new one based on distance, are compared to determine which of these can result in the most accurate driving cycle. The results show that the microtrips based on spatial characteristics provide more representative driving cycles, while amongst the different spatial characteristics, distance-based approaches resulted in the most accurate driving cycles.

In the final chapter, Chapter 7, a review of the main findings of this research is provided. Also, considering that certain limitations and challenges were faced during this study, we also discuss those briefly. The process of estimating emissions is a work in progress, and while it has evolved over the past decades, there is still room for improvement and furthering our understanding and analytic tools. In the last section, some recommendations for future studies are offered.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

AC	Air Conditioning
ARTEMIS	Assessment and Reliability of Transport Emissions Models and Inventory Systems
CCAP	Climate Change Action Plan
CCF	Congestion Correction Factor
CECERT	College of Engineering Center for Environmental Research and Technology
CMEM	Comprehensive Modal Emissions Model
CNG	Compressed Natural Gas
COPERT	Computer Program to calculate Emissions from Road Transport
EC	Engine Capacity
EMFAC	Emissions Factors
EV	Electric Vehicle
FC-VSL	Fuel Consumption- Variable Speed Limit
GHG	Greenhouse gases
GPS	Global Positioning System
GUI	Graphical User Interface
GWP	Global Warming Potential

HBEFA	Hand Book Emissions Factors for Road Transport
HDV	Heavy-Duty Vehicle
HOV	High Occupancy Vehicle
IPCC	Intergovernmental Panel on Climate Change
IRI	International Roughness Index
ISA	Intelligent Speed Adaptation
IVE	International Vehicle Emissions
LCO	Life Cycle Optimisation
LOS	Level Of Service
MOVES	Motor Vehicle Emissions Simulator
MPD	Mean Profile Depth
MTQ	Ministry of Transportation Quebec
OTAQ	Office of Transportation and Air Quality
PEMS	Portable Emissions Measurement System
PHEM	Passenger car and Heavy-duty Emissions Model
RR	Rolling Resistance
RRC	Rolling Resistance Coefficient
SI	Spark ignition

SP	Specific Power
TDM	Travel Demand Management
TEE	Traffic Emissions and Energy
U.S.	United States
USEPA	United States Environmental Protection Agency
VKT	Vehicle Kilometers Traveled
VSP	Vehicle Specific Power
VTI	The Swedish National Road and Transportation Research Institute
WCI	Western Climate Initiative
ZEV	Zero Emissions Vehicle

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

"*Chart-topping June extends Earth's warmest period on record*"

(Samenow, 2015)

This somewhat incendiary headline echoes so many others in recent years, reporting the record-breaking weather conditions such as heat, cold, rainfalls, droughts, etc. When was the last time you heard about climate change or global warming? The subject has become a hotly debated question in scientific and political circles, with one question frequently arising: On whom, or where, can we place the blame?

1.1 Context

Climate change has become the top environmental concern over the past few decades. It is believed that the increase in the level of Greenhouse Gases (GHG) in the atmosphere is the main factor, and that the transportation sector can be traced back as the main contributor, specifically in North America (Atkins, 2009). In addition to climate change, the emissions coming from means of transportation can also affect air quality, noise level, water quality, soil quality, biodiversity, and land take (Rodrigue, Comtois, & Slack, 2013). Therefore, reduction in emissions from transportation has jumped to the beginning of the list of top priorities for almost every government. But what, exactly, is climate change? What are the consequences? How does transportation contribute to climate change? All these questions will be discussed in this introduction.

1.1.1 Climate change

As mentioned, climate change dilemma has become the first environmental challenge during the recent decades. We hear about climate change and its consequences almost every day. But how do we define climate and the anomalies of the climate?

Climate is basically referred to as the average weather conditions such as temperature, rainfall, wind direction and wind speed over the period of 30 years (B. Metz, 2010). Therefore, climate change is “a change in statistical properties of weather and climate at a place, in terms of average, variability, or both” (Arnell, 2015, p. 15). The primary indicator of climate change is the rise in the global temperature, that’s why it is often referred to as global warming. However, its consequences do not limit to the rise in the local temperature; contradictorily enough, the extreme cold can also be among the consequences. Figure 1.1 demonstrates the global land-ocean temperature variations since 1880. The records show a constant rise that has started more clearly around 1910s; the increase has been more dramatic since 1980s.

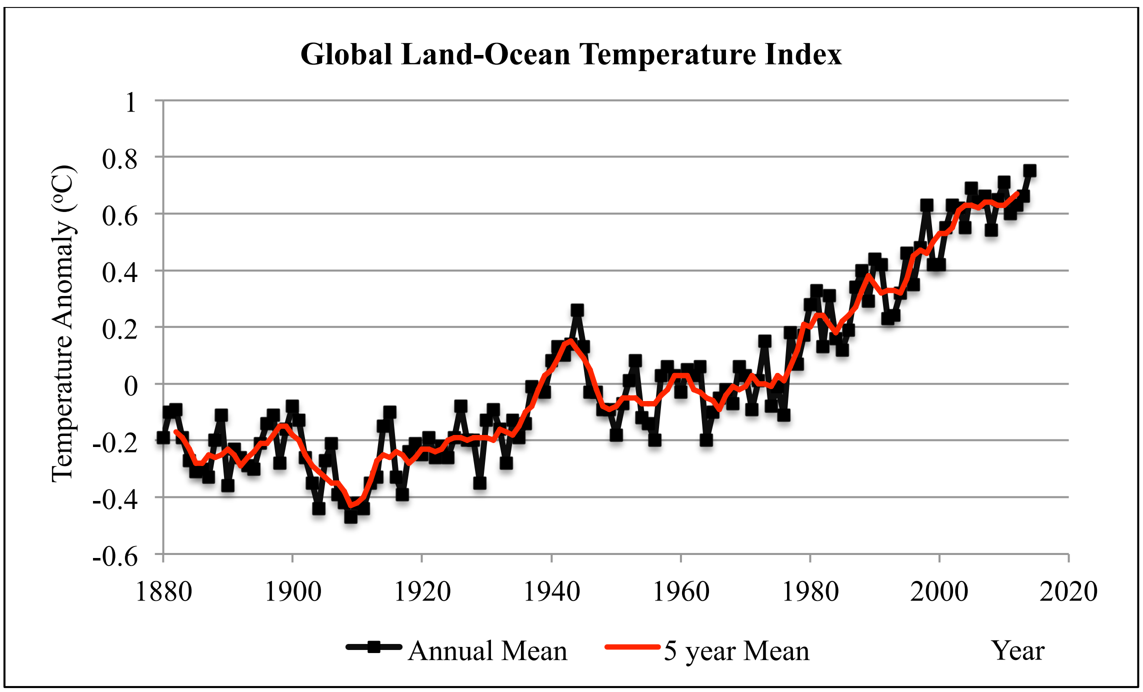

Figure 1.1: The global land-ocean temperature index (reproduced from: Hansen & Schmunk, 2011)

In addition to the temperature, climate change has a major influence on the environment; some of the main impacts are rise in the sea levels, multiplication of extreme weather events, the melting of glaciers, drought, and downpours. Some of these changes are irreversible such as the melting of glaciers and the extinction of species due to changes in their habitats (B. Metz, 2010). This fact emphasizes the immediate need to take action to avoid further damage. The first step towards defying climate change is identifying the main causes.

The causes of climate change can be classified in two categories: natural and anthropic. The main natural causes are solar radiation variations and volcanic eruptions. However, they are believed to be insignificant comparing to the anthropic causes. Scientists credit the raise in greenhouse gases (GHG) present in the atmosphere, produced by human activities, as the main guilty party for climate change (Crowley, 2000; B. Metz, 2010).

Initially, the greenhouse gases do not have a negative impact on the earth; to the contrary, in normal levels, the concentration of greenhouse gases in the atmosphere regulates the temperature on earth. In fact, without them the earth would have been too cold for any living organisms to survive. Therefore, greenhouse gases are responsible for making the earth suitable for life due to the natural greenhouse effect they create. However, if the level of greenhouse gases rises, the temperature will rise as well; the earth is able to recover from just a certain amount of surcharge. But if the level increases faster than the natural trend (i.e. the enhanced greenhouse gas effect), the earth cannot cope with this surcharge and results in extreme conditions (Leroux, 2005).

The main greenhouse gases are water vapour (H_2O), Carbon dioxide (CO_2), Methane (CH_4), Nitrous oxide (N_2O), Ozone (O_3), Chlorofluorocarbons (CFCs), and carbon tetrachloride (CCl_4) (R. T. Watson, Meira Filho, Sanhueza, & Janetos, 1992). Among those, Carbon dioxide is the most important anthropogenic greenhouse gas since it is produced significantly more than any other GHG (Intergovernmental Panel On Climate Change, 2007).

In the analysis of the impact of the greenhouse gases two measures are considered: the Global Warming Potential (GWP) and the lifetime in the atmosphere. GWP represents the cumulative radiative capacity of the gas to trap the heat in the atmosphere, relative to CO_2, and the lifetime is the period that they can stay in the atmosphere before decomposing (Murshed, 2010). It is important to note that the GWP of the gases usually changes over time and therefore its value is usually followed by the time it has been present in the atmosphere. Table 1.1 provides the 100-year GWP and the lifetime of some of the main regulated[1] greenhouse gases. As we can see, some gases can stay in the atmosphere for hundreds of years.

Table 1.1: GWP and lifetime of the main greenhouse gases (IPCC, 2007)

Name of gas	Chemical formula	Atmospheric lifetime (years)	100-year GWP
Carbon dioxide	CO_2	50-200	1
Methane	CH_4	9-15	21
Nitrous oxide	N_2O	114	310
Hydrofluorocarbons	HFCs	1.4 - 270	140 – 11,700
Chlorofluorocarbons	CFCs	45 – 1,700	3,800 – 8,100
Carbon tetrachloride	CCl_4	26	1,400

The recent analysis of the Intergovernmental Panel on Climate Change (IPCC) in the 4th assessment report indicates that a 50% to 80% reduction of global GHG emissions by 2050, from the year 2000's levels, is required to avoid serious consequences (Ohnishi, 2008). Since the 1990s, different national and international frameworks have been proposed to reduce greenhouse gases; in the following section a brief review of those will be provided.

1.1.2 Policies regarding the GHG emissions reduction

The Kyoto Protocol is the only international and legally binding agreement to tackle climate change so far. It commits its parties to achieve an international goal for the reduction of greenhouse gas emissions (United Nations, 2015). The protocol was adopted in Kyoto, Japan in 1997 and entered in force in 2005. The first commitment period started in 2008 and ended in 2012. Based on the Kyoto Protocol, the countries contributing to an overall 55% of the GHG emissions, approved to respect a certain target. However, among

[1] The gases that are measured and monitored

them the United Stated[2] and Australia did not accept to commit (Sperling & Cannon, 2007).

After the first round, the new commitment, referred to as the "Doha Amendment to Kyoto Protocol", was adopted in 2012. Based on this amendment, 37 industrialized countries agreed to reduce their GHG emissions 18% below the 1990 level in an eight-year period from 2013 to 2020 (United Nations, 2015). Initially Canada was among the countries that committed to the protocol but withdrew in 2011 (Curry & McCarthy, 2011).

However, despite the withdrawal of Canada, Quebec was the first province to take action toward GHG emissions reduction and to push ahead with its climate change action plan (Teisceira-Lessard, 2011). Comparing to the other Canadian provinces, Quebec is among the least emitters (Figure 1.2).

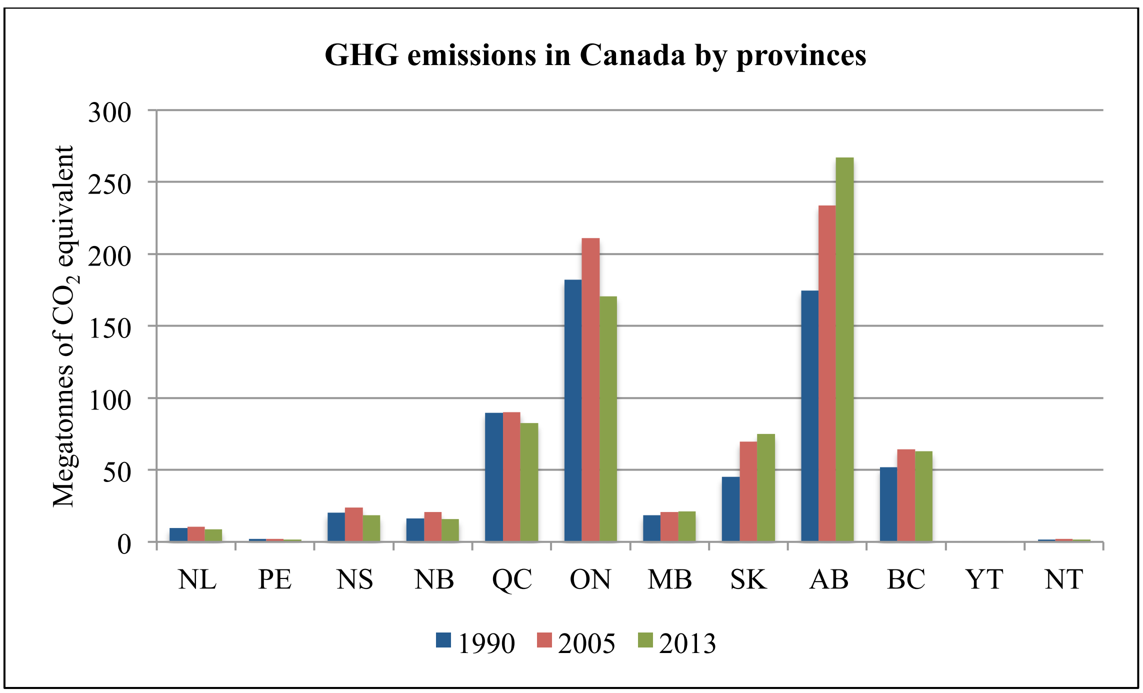

Figure 1.2: Total GHG emissions per province (Environment Canada, 2010)

[2] U.S. is second largest CO_2 emitter after China and responsible for about 16% of the global CO_2 emissions.

Based on the province of Quebec's action plan, the objective is to reduce the GHG emissions to 20% below the 1990 level by the year 2020. Quebec's commitment to achieving its goal follows the 2006-2012 Climate Change Action Plan (CCAP 2006-2012) adopted in the Kyoto Protocol framework. As a part of this action plan, Quebec has established a carbon market ("Québec in action!," 2012), a program coordinated with the Western Climate Initiative (WCI), a North American organization focused on tackling climate change. Through the first phase, starting on the 1st of January 2013, large industrial emitters are obliged to comply with the program. In its second phase, starting from January 2015, enterprises that distribute or import fossil fuels in Quebec will also have to comply with the system ("Québec in action!," 2012). In a carbon market or cap-and-trade system, basically, each enterprise has a certain allowance to produce GHG emissions. If they produce more, they have to buy more allowance from the carbon market to cover their surcharge and if they produce less they can sell the extra allowance.

It is at this point that we became familiar with some of the main emissions reduction programs on an international level, as well as national and provincial. The next step to decrease the GHG emissions is to identify the main contributors.

1.1.3 Who is responsible for the GHG emissions

From a global perspective, the energy supply contributes the most to the GHG emissions, being responsible for about 26%. After that, industry, forestry, and agriculture are the biggest emitters, followed by transport, buildings and waste (B. Metz, Davidson, Bosch, Dave, & Meyer, 2007). Also, among all the greenhouse gases, the share of CO_2 is the highest (about 77% of the total GHG).

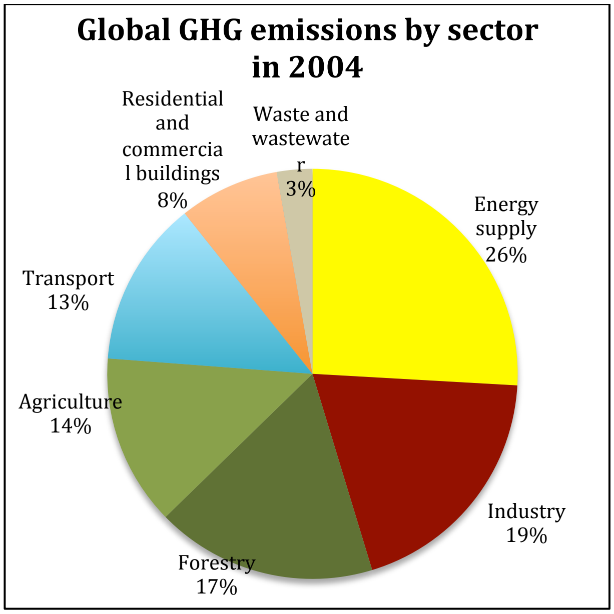

Figure 1.3: GHG emissions by sector in 2004 (B. Metz et al., 2007)

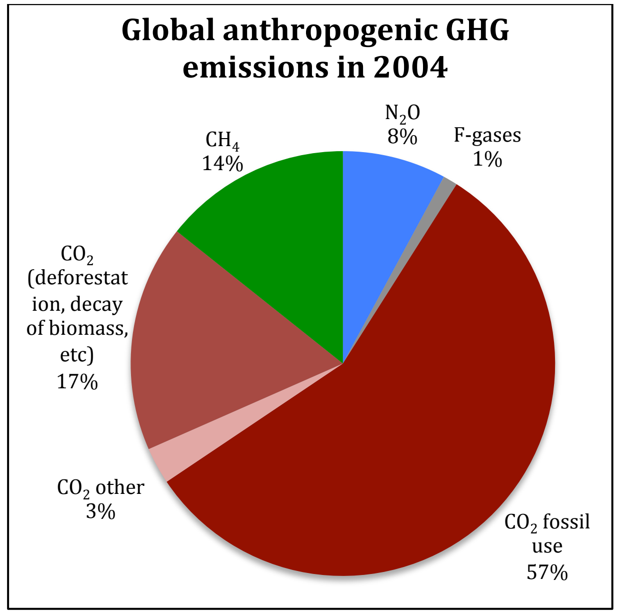

Figure 1.4:Global anthropogenic GHG in 2004 (B. Metz et al., 2007)

However, the share of each sector is different in different regions. Specifically, the source of electricity has a very significant influence on the contribution of each sector. For example, in Quebec, about 45% of greenhouse gases emissions is produced by transport, and among different gases, CO_2 amounts to 80% of it (Delisle, Leblond, Nolet, & Paradis, 2015).

The main focus of this study is the province of Quebec; and knowing that the transportation sector is the main contributor in Quebec and CO_2 having the highest share among the different greenhouse gases, this study is focused on the CO_2 emissions from the transportation sector. In the following section, policies and strategies regarding emissions reduction in transportation sector will be reviewed.

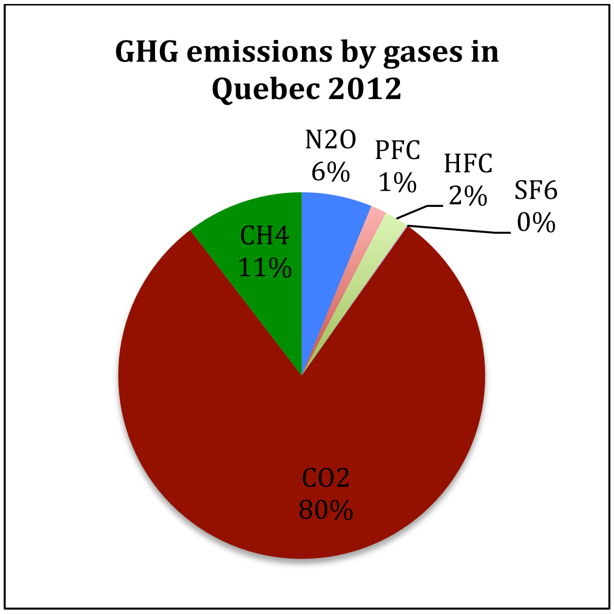

Figure 1.5: GHG emissions by gas type in Quebec in 2012 (Delisle et al., 2015)

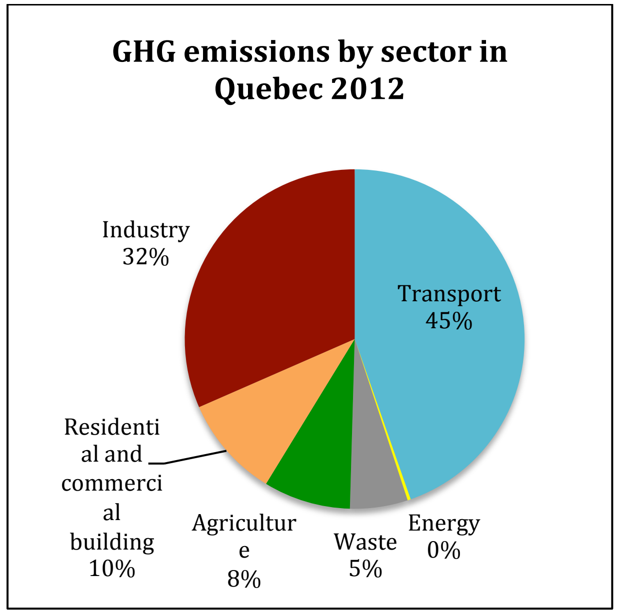

Figure 1.6: GHG emissions by sector in Quebec in 2012 (Delisle et al., 2015)

1.1.4 CO_2 emissions reduction strategies in transportation sector

Before discussing further, it is important to mention that CO_2 emissions are proportional to the fuel consumption; each litre of gasoline produces 2.4 kg of CO_2 on average. Therefore, the fuel consumption and CO_2 emissions is often used interchangeably in this study. The following equation demonstrates the general chemical equation of complete gasoline combustion.

$$n_1C_XH_Y + m_1O_2 \rightarrow n_2H_2O + m_2CO_2$$

Equation 1-1

In general, the amount and variability of emissions from transportation is influenced by four main elements: travel demand, mode share, fuel type, and fuel economy (Ohnishi, 2008). Keeping that in mind, reduction in emissions can be achieved by making modifications to these elements. Therefore, an integrated transport policy for emissions reduction would consist of the following methods (B. Metz, 2010):

1. Reduce demand: lower need for transport

2. Shift means of transport: shifting to less emitting modes such as active transportation
3. Change the fuel: shift from oil products to less polluting and less carbon intensive fuels
4. Improve efficiency: reduce the fuel consumption of vehicles

Each of these elements is broken down to the more tangible policies in the following sections.

1.1.4.1 Travel demand and mode shift

Private vehicle ownership has been increasing around the world and, consequently, the energy consumption and emissions are continuing to increase (Poudenx, 2008). Undoubtedly the best way to decrease emissions would be decreasing the trips or changing the mode towards more efficient modes. Since most of the strategies for emissions reduction touch upon both travel demand and travel mode, we discuss both, together, in this section.

The first and most important measure to reduce vehicle emissions is to reduce vehicle activity; fewer Vehicle Kilometers Traveled (VKT) results in less emissions. In the early 1970s in the United States, due to the booming travel demand, the transportation policy makers started to think of how to satisfy the increasing demand without increasing the capacity and building more roads (Meyer, 1999). Travel Demand Management (TDM) programs came into being with an aim to use the most out of the available network. Some of the proposed TDM policies are (Gärling et al., 2002):

1. Taxation of cars and fuels
2. Closure of city centers for car traffic
3. Road pricing
4. Parking control
5. Decreasing speed limits

6. Avoiding major new road infrastructure
7. Teleworking
8. Land use planning that encourages shorter travel distances
9. Traffic management reallocating space between modes and vehicles (e.g. bus and high occupancy vehicle lanes)
10. Park and ride schemes
11. Improved public transport (e.g. frequency, comfort, retrievability of information about public bus and high occupancy vehicles lanes)
12. Improved infrastructure for walking and biking
13. Public information campaigns about the negative effects of driving
14. Social modeling where prominent public figures use alternative travel modes

The impact of these strategies largely depends on the travel behaviour and the specific characteristics of each region. For example, in a study of comparison of the TDM strategies in the U.S. (Meyer, 1999), it is discussed that the congestion pricing has the highest impact on the number of trips, whereas the bike/pedestrian infrastructure has a very low impact.

Also Gärling and Schuitema (2007) believe that coercive measures such as pricing have more impact on trip reduction; however, when it is paired up with the non-coercive measures, it is the most effective. The road pricing in London is considered one of the successful examples, which could reduce CO_2 levels by 20% by reducing the vehicle trips (Beevers & Carslaw, 2005)[3]. In addition to the reduction in the total private vehicle trip, increasing the fees can encourage a mode shift. The mode shift toward the active transportation can have a significant impact on reducing the vehicle use.

[3] They examined the impact of the pricing on emissions through changes in speed profile, but they found it insignificant comparing to the impact of the reduced VKT.

Godefroy and Morency (2012) estimated the potential of about 18% reduction in private vehicle trips, in Montreal (Quebec), by replacing them with bike and walk. In their study they considered the geographical, demographic, and travel behaviour to calculate the feasibility of biking or walking. However, sometimes the personal preference makes a big difference; many prefer to drive despite the fact that walking or biking is a viable alternative.

Another strategy that can have an important influence on emissions, specifically through a reduction in the number of trips, is telecommuting. A comparison of participants' telecommuting day travel behaviour with their before-telecommuting behaviour in Australia shows a 27% reduction in the number of personal vehicle trips, a 77% decrease in VKT, and 39% (and 4%) decreases in the number of cold (and hot) engine starts (Koenig, Hensher, & Puckett, 2007). All these changes can have a significant reduction on emissions. Overall, the strategies that result in the lower VKT or mode shift are considered the most effective regarding the GHG emissions.

1.1.4.2 Fuel type

Along with the change in travel demand and mode, fuel is one of the main determinants of the vehicle emissions levels. The research on more efficient and less pollutant fuels is numerous, and as a result various alternative fuels have been introduced and evaluated. In general, fuels can be classified in two categories: conventional fuels and alternative fuels. In road transportation, conventional fuels refer to gasoline and diesel. Historically, in comparing these two fuels regarding their contribution to CO_2 emissions, it has been believed that the diesel engine produces less CO_2 for the same power output. Yet, due to recent improvements to the gasoline engine efficiency this gap has been reduced (Sullivan et al., 2004). Nevertheless, diesel and gasoline are both fossil fuels, and come with a high carbon concentration. Considering the urgent need to reduce the carbon emissions, more and more studies are focused on the types of fuels with a lesser carbon content.

Some of those main alternative fuels are: biodiesel, bioethanol, hydrogen cell, solar energy, compressed natural gas, and electricity. Each of these alternative fuels has its advantages and disadvantages. To evaluate the alternative fuels, from the provider's perspective, the following factors are commonly considered (Jahirul et al., 2010):

15. acceptability of fuel supply,
16. process efficiency,
17. ease of transport and safety of storage,
18. vehicle modifications needed, and
19. fuel compatibility with vehicle engine (power, emissions, ease of use, and durability of engine)

In addition, from the users' perspective, some of the challenges of the alternative fuels consist of (Romm, 2006):

- the higher cost of the vehicle,
- on-board fuel storage,
- safety and liability,
- high fuelling cost, and
- limited fuel stations.

For example, solar powered engines are not market adaptive yet and require further research on the design of the engine (Jahirul et al., 2010). Also, regarding the hydrogen engines, the volumetric efficiency is much less than that of gasoline-powered engines (White, Steeper, & Lutz, 2006). Besides there are important safety concerns over the transportation and storage of the fuel (Chalk & Miller, 2006).

Meanwhile, there are some other alternative fuels that are easier to adopt such as biodiesel and bioethanol that require minor to no engine modification. Bioethanol, specifically, could provide a fuel with no carbon dioxide emissions (Lave, MacLean, Hendrickson, & Lankey, 2000). In addition, mixing ethanol with gasoline can also provide carbon reduction benefits. For example 85% of ethanol (E85) can reduce emissions by 70%

(USEPA, 2006). However, taking the engine performance in to account, a 20% blend offers the best performance and still reduces CO_2 emissions by 7.5% (Al-Hasan, 2003).

Biodiesel, on the other hand, does not reduce the CO_2 emissions but also increases the fuel consumption and CO_2 emissions due to deteriorated engine efficiency. In the case of biodiesel the impact largely depends on the driving behaviour and the engine load; the least efficient events were observed under low speed, in low load condition (Fontaras et al., 2009). However, regarding the lifetime assessment, both bioethanol and biodiesel have brought up certain concerns regarding the environmental impact and the threat to food security (Escobar et al., 2009).

Furthermore, it is discussed that Compressed Natural Gas (CNG) can represent a good alternative fuel for Spark Ignition (SI) engines and can be the future fuel for transportation and has become very popular in some countries. The CNG can reduce the CO_2 by up to 20% and requires minor modifications to the conventional spark ignition engine (Gopal & Rajendra, 2012).

In addition, the introduction of the Electric Vehicles (EV) as Zero Emissions Vehicles (ZEV) seems to be the ultimate solution for emissions reduction. However, the source and the processing of energy production and storage, as well as the lifetime of the vehicle, play an important role in defining the benefit of these types of vehicle. The EV vehicles can only be environmentally beneficial if the electricity is produced from low carbon sources (C. Samaras & Meisterling, 2008). Otherwise, it is claimed that the electricity being produced by high carbon sources can even increase the life cycle carbon emissions since the electric engines are not very energy efficient (Helms, Pehnt, Lambrecht, & Liebich, 2010).

The cost and benefit analysis of the electric vehicles is a sensitive subject. The methodology of the life cycle assessment of the electric vehicles can play a significant role in determining its benefits. In one study, it is discussed that just by overestimating the lifetime of the EVs, the benefit has been overestimated by about 28%; whereas, the environmental benefit can be reduced by up to 14% in case of more realistic lifetime assumptions (Hawkins, Singh, Majeau-Bettez, & Strømman, 2012). However, it is important to note that all estimations can change significantly in different regions due to the difference in the source of electricity production and geographical and climatic characteristics. Also, due to the rapid advancement of the EV technology, the assessments require regular updates.

It should also be noted that although the new technologies in vehicle and fuel can decrease the fuel consumption, any transformation in the fleet would be gradual. Every year only 7% of the in-use vehicles are replaced by new vehicles (Barkenbus, 2010) and among those a small percentage is dedicated to low carbon emissions vehicles. The process of moving toward alternative fuels could take decades; therefore, it is important to keep working on improving the conventional fuel vehicles in parallel to introducing and implementing new vehicle technologies.

In Canada more than 80% of the energy used in transportation (passenger, freight and off road) is based on gasoline and diesel, which confirms the importance of these fuels in emissions reduction strategies. Table 1.2 shows the share of each fuel type in the total energy production across Canada, which includes passenger, freight and off-road (Statistics Canada, 2014).

Table 1.2: Share of different fuel types in energy production in transportation in Canada 2012

Energy source	**Share**
Electricity	0.15%
Natural Gas	0.07%
Motor Gasoline	53.22%
Diesel Fuel Oil	32.30%
Ethanol	2.68%
Heavy Fuel Oil	2.56%
Aviation Gasoline	0.10%
Aviation Turbo Fuel	8.43%
Propane	0.50%

Regarding motor gasoline, there are some improvements that can be made to reduce the CO_2 emissions such as modifying the levels of sulphur inherent to the gasoline and of the detergent additives. In a cost and benefit analysis of the introduction of the sulphur free

(<10 ppm) fuels by the European Comission (2001), it is discussed that the modification can reduce the total CO_2 emissions by 347.1 kt, even considering the additional emissions produced by the refineries themselves; another 3% improvement in fuel economy is also observed through the use of detergent additives to the fuel (Karpov, 2007). However, Canada falls behind in this matter and has set the required gasoline sulphur level to a yearly pool average of 30 ppm, with a maximum of 80 ppm, which is much higher than the European legislation (Row & Doukas, 2008). Therefore the quality of the fuel is one of the factors that still can be enhanced, especially in certain locations.

As mentioned above, gasoline is the most popular fuel used in North America and the shift towards alternative fuel is gradual and might even take decades. Therefore, this study is focused on the regular SI gasoline vehicle. However, it is necessary to keep in mind other possibilities, although analyzing all the fuel types or transportation modes would not fit into this study. So far, the travel demand, travel mode and fuel type have all been discussed briefly. In the following section, the subject of vehicle economy and the policies regarding emissions reduction through the improvement of fuel economy of the gasoline passenger vehicles will be discussed in more detail.

1.1.4.3 Vehicle fuel economy

The shift towards greener fuel or a reduction in travel demand can be a slow process, mainly due to the high costs of infrastructure (especially in the case of fuel) and acceptability of the projects (both regarding the modification of the travel behaviour or mode and the fuel shift). Meanwhile, other policies and strategies should be taken into consideration. The strategies can be classified in two categories; the first category focuses on improving the fleet by improving the new vehicles' technologies and removing the old cars from the fleet. The second category of strategies mainly has a direct or an indirect impact on vehicle utilisation and driver behaviour. In this section, both categories and the main relevant strategies will be looked at.

In the first category, the strategies regarding the vehicle's characteristics consist of the policies that can affect vehicular emissions by regulating or modifying the vehicle, and are independent of the vehicle utilisation factor or driver behaviour. The most significant of those are the regulations and standards set by the governments aimed at the vehicle manufacturers. These regulations are focused on improving the vehicle economy through the improvement of vehicular technology. Also, encouraging the scrapping of old cars currently still in-use is a complimentary regulation to improve the fuel efficiency of the entire fleet in a shorter period. Policy makers are mainly pushing for more efficient vehicles, alternative fuels and reducing kilometers traveled. However, as mentioned earlier, modifying the fleet can be a slow process. Meanwhile, there are other strategies that can help reduce the vehicle CO_2 emissions with the current fleet characteristics.

The second category of strategies, mainly influencing the driving pattern, can be approached with two different perspectives: traffic management and eco driving. While traffic management strategies are the ones conducted by the authorities, eco-driving is among the strategies adopted by the drivers themselves. All, these strategies will be introduced in this section.

Regulations for manufacturers

First and foremost, in a larger scale, the national governments are responsible to oblige the vehicle manufacturers to produce more fuel-efficient vehicles. The vehicles' pollution emissions standards have been around for a while but it is only recently that the GHG emissions became regulated. In Canada, the first *Passenger Automobile and Light Truck Greenhouse Gas Emissions Regulations* was established in 2010 to reduce the greenhouse gas emissions by setting emissions standards and test procedures that were aligned with the regulations in the U.S. This new regulation required the automobile makers to reduce the GHG emissions of their fleet starting in 2011 through 2016.

The more recent amendment to this regulation regards the vehicles from 2017 and beyond, and aims to reduce the GHG emissions of the fleet by 50% in 2025, comparing to the level from 2008. Based on that, over the lifetime operation of 2017 to 2025 model year vehicles, the regulation is projected to deliver the total GHG reductions of 174 megatons, roughly equivalent to one year of GHG emissions from Canada's entire transportation sector (Environment Canada, 2014). However, without eliminating the old high-consumption vehicles, the improvement of the fuel efficiency of the entire fleet can be slower; therefore it is necessary to implement a complimentary regulation for scrapping the old vehicles at the same time.

Scrapping old cars

It is expected that, not considering other factors, the shorter the average lifetime of the vehicle is, the lower the energy consumption and emissions would be; this is all considering the older vehicles produce higher emissions because of the degradation of their emissions control systems[4] (Lawson, 1993; Ntziachristos & Samaras, 2000; Z. Samaras et al., 1998; Zachariadis, Ntziachristos, & Samaras, 2001). Programs intended for scrapping old cars have been introduced in the 1990s in many countries to reduce vehicle emissions from the more emissions-prone older vehicles. However, all is not as simple as that. It is true that the older vehicles have higher emissions rates, but at the same time, the process of making new vehicles or scrapping the old vehicles also produces high emissions.

With this in mind, it is crucial to assess the life cycle emissions rather than just the tailpipe emissions. If the vehicles are scrapped earlier than their efficient lifetime, the whole process can produce even more emissions unless the trend of fuel economy improvement changes much faster than the historical data would indicate (Van Wee, Moll, & Dirks, 2000). In the same study, the authors mentioned that in an evaluation of the life-cycle energy requirements of new cars in the Netherlands between 1990 and 1994, 15 to 20% of the life-cycle energy requirement is linked to car production, maintenance and disposal; the remaining 80 to 85% is related to the fuel consumption for car driving. Therefore, it is very important to determine the most efficient lifespan of the vehicles. The

[4] However, no significant relation between the mileage and CO_2 emissions has been found (P. Boulter, 2009; P. Boulter, Barlow, & McCrae, 2009; Ntziachristos & Samaras, 2000)

analysis highlights that the newer vehicles on the road do not necessarily result in less global emissions.

There are several life cycle assessment tools and approaches to analyze the lifespan of the vehicles. In one study of calculating the optimised life cycle of the vehicle, it is discussed that the optimal life of the vehicle regarding the cumulative CO_2 emissions is 18 years, based on driving 12,000 km/year (Kim, Keoleian, Grande, & Bean, 2003). In their study, they applied the Life Cycle Optimization (LCO) model to mid-sized passenger car models between 1985 and 2020. It is important to note that these numbers cannot be generalised; each region can have its own optimal vehicle lifespan depending on the local fleet and even the environmental characteristics.

In addition to the composition of the fleet, the Vehicle Kilometers Traveled (VKT) can play an important role in the total fleet emissions. For example, it is believed that older vehicles are driven less (Van Wee et al., 2000); therefore, they can have a less important share in the global emissions.

Traffic management

In regards to emissions reduction, traffic management strategies can consist of three main perspectives: congestion mitigation, speed management, and traffic smoothing. Most of the strategies touch on all three perspectives at the same time and can hardly be discussed separately. Traffic congestion is a very hot topic in traffic engineering and transportation planning. However, it is largely overlooked as a solution for reducing CO_2 emissions. As a simplistic approach, when congestion increases, vehicles drive for longer time and therefore the fuel consumption and CO_2 emissions increase accordingly. In addition, traffic management strategies not only have influence on travel time, but also impact the driving behaviour elements such as speed and the frequency of acceleration/deceleration. There are various strategies to decrease the traffic congestion and improve the traffic fluidity. Various studies have claimed that traffic signal timing and coordination is among the most common traffic management strategies that can improve fuel consumption or reduce CO_2 emissions significantly (Unal, Rouphail, & Frey, 2003). For example, in one study using a traffic simulation model (VISSIM) for a signal coordination on a highway, the authors reported a 9% of CO_2 emissions reduction (Zhang et al., 2009). Also in another study, again using a microsimulation model, it was observed that the coordinated traffic light that creates green waves along major arterials is not only beneficial for CO_2 emissions reduction, but also in lowering air and noise pollution by reducing the acceleration and deceleration of vehicles (De Coensel, Can, Degraeuwe, De Vlieger, & Botteldooren, 2012).

The traffic management strategies are usually focused on increasing the vehicles' speed; however, it is important to note that a higher speed does not necessarily mean lower emissions. On the contrary, if the vehicles drive too fast on the highway, that can increase fuel consumption due to the increased aerodynamic resistance of the vehicles. The speed and fuel consumption per kilometer has a U-shaped relation, meaning that the fuel consumption decreases by the increase of the speed to an optimal level (about 80 km/h) and it starts to increase after. The optimal speed however can be different depending on the technology of the vehicle engine and its aerodynamics. Also, higher speed can mean more frequent and brusquer acceleration and deceleration. In order to avoid that, Intelligent Speed Adaptation (ISA) has been introduced.

ISA is basically an in-vehicle electronic system that enables the speed regulation; it is connected to a GPS and map, and whenever the speed exceeds the posted speed the fuel is cut off. However, in an analysis of the ISA method, Int Panis, Broekx, and Liu (2006) discussed that the benefit of the ISA is dependent on the situation and they did not find any statistically significant impact on the CO_2 emissions. In another study, a similar but more intricate scheme has been analyzed. In that study, Bojin, Ghosal, Chen-Nee, and Zhang (2012) introduced a carbon foot print/ fuel consumption-aware variable speed limit (FC-VSL) that regulates the speed based on various measures, such as road conditions, and communicates in real time with the road-side infrastructures that are connected to a control center, which evaluates the road conditions and determines the optimal speed. Their results of the study showed that in contrast to ISA, this method could bring significant improvement on fuel consumption or CO_2 emissions due to the traffic smoothing effect that it offers.

Another traffic management strategy for smoothing the traffic flow is through the replacement of signalized intersections with roundabouts. It is claimed that this strategy can reduce fuel consumption by 28% and 3% for replacing signalised yield-regulated junctions (Várhelyi, 2002). In this study, the author studied 20 yield-regulated intersections and 1 signalised intersection that were converted to roundabouts to improve the safety. Also, in another study with more samples, in Kansas and Nevada, Mandavilli, Rys, and Russell (2008) confirmed the results of the previous study and presented even higher benefits (16-59%) both for AM and PM peak periods. However, Ahn, Kronprasert, and Rakha (2009) in another effort explained that the environmental benefit of the roundabout depends on the road type and demand. They explained that at the intersection of a high speed and a low speed road, the roundabout does not necessarily reduce fuel consumption. In their case study, the roundabout reduced the delay and the queue length at the intersection but the high acceleration following the roundabout increased fuel consumption considerably. As a result, the roundabouts are most efficient when approaching traffic volumes are relatively low. However, even in low speed traffic, when demand increases it can result in a substantial increase in delay comparing to the signalised intersections.

In addition to the intersection design, in the same category of road design, there's also some evidence that the lane's layout might have an influence on fuel consumption. For example in a study of High Occupancy Vehicle (HOV) lanes in California, it is revealed that a constant access to a HOV lane produces less CO_2 emissions and that's mainly due to the highly concentrated manoeuvring on the dedicated ingress/egress sections, which causes higher frequency and magnitude of acceleration and deceleration (Boriboonsomsin & Barth, 2008).

It is important to mention that the environmental assessment of the traffic management strategies is very complex and requires detailed analysis of the driving behaviour and cannot only depend on the improvement of the average speed. Both acceleration and deceleration can play an important role in the fuel economy. This is why most recent studies try to assess the traffic and its impact on fuel consumption using the Level Of Service (LOS) rather than the average speed. The LOS indicates the observed speed comparatively to the posted speed. In addition to the speed, LOS can provide further information on the traffic conditions. Different traffic conditions can result in specific driving behaviours. For example, in lower LOS, higher numbers of acceleration and deceleration can be observed.

In an analysis on fuel consumption based on the LOS, using a travel demand forecasting model for Grover Beach, CA, it is demonstrated that the LOS B provides the lowest fuel consumption, whereas LOS D and C resulted in the highest. However, when it comes to intersections the lowest fuel consumption was achieved in LOS A (Cobian, Henderson, Mitra, Nuworsoo, & Suvillan, 2009). To this point, most of the policies introduced are considered as compelling, but the drivers also can contribute to the emissions reduction, which can be mainly achieved by increasing their awareness and sensibility; eco-driving programs are mainly focused on this subject.

Eco-driving

All driving trip consists of idling, acceleration, cruising, and deceleration, also the proportion and the frequency of time spent in each mode depend on the driver's behaviour, whether it is aggressive or mild. Therefore, the driving behaviour can have a significant influence on fuel economy and vehicle emissions. Although individual effort may seem trivial in GHG emissions, an aggregated result can be significant. There are different studies that confirm the possibility of substantial contribution of the individuals (Barkenbus, 2010; Bin & Dowlatabadi, 2005; Vandenbergh, Barkenbus, & Gilligan, 2008; Vandenbergh & Steinemann, 2007).

In transportation, in addition to the decrease in VKT, individuals can reduce their vehicle's GHG emissions through modification in their driving behaviour, which is usually named as eco-driving. Eco-driving can be classified in two categories: speed related behaviour, and utilisation and maintenance. Regarding the speed related measures it is suggested to:

- accelerate moderately,
- anticipate traffic flow and signals to reduce the sudden stop and go behaviour,
- maintain a steady speed (using cruise control in highways),
- drive safely below the speed limit,
- shift gear as soon as possible (Saboohi & Farzaneh, 2009),
- avoid excessive idling (Barkenbus, 2010).

It is discussed that depending on the road type and vehicle technology, aggressive driving can increase the fuel consumption by 40% comparing to normal driving (De Vlieger, 1997; De Vlieger, De Keukeleere, & Kretzschmar, 2000). Also in another study of 400 vehicles in Denver, 10% fuel consumption reduction were achieved through education and monitoring effort considering the speed related measures (Barkenbus, 2010).

The second category of strategies, which is more related to utilisation of the vehicle rather than driving behaviour, consists of modification in route choice, decrease in the use of air conditioning, keeping the vehicle in indoor parking to reduce the excess cold start emissions, and even maintaining an optimum tire pressure (Velupillai & Guvenc, 2007). Depending on the region's characteristics each of these factors can have a different influence on emissions. For example, in warmer areas the use of AC can result in a significant increase in fuel consumption. It is reported that, in India, about 20% of the fuel consumption is related to the use of Air conditioning (Chaney, Thundiyil, Andersen, Chidambaram, & Abbi, 2007).

Also, drivers usually pick a route that minimized their travel time, which may result in traveling longer but faster and we mentioned earlier that the shorter the trip in time the less emissions we will produce. However, Ahn and Rakha (2008) in a study of route choice, using microscopic and macroscopic emissions model, discussed that the faster highway option is not always the best route regarding the environmental perspective. The contribution also depends on the type of the vehicle. For example, high emitting vehicle produce much more GHG emissions in low speed and high frequency acceleration (congested traffic), whereas low emitters produce much lower emissions comparing to their emissions in normal driving condition and sometimes higher on highways. As a summary of their study, they indicated that choosing a fuel-efficient route can significantly reduce fuel consumption. However, it requires a more dedicated calculation and cannot be decided with a generalized rule of thumb.

1.1.4.4 Summary of emissions reduction strategies

In this section various emissions reduction strategies were presented, each of the strategies have a certain level of effectiveness, advantages and disadvantages as well as costs. Table 1.3 provides a brief summary of the strategies discussed in this section. It is however impossible to draw a general conclusion on their comparative analysis. The results are specific for each territory and require an extensive amount of information and analysis.

Table 1.3: Summary of the emissions reduction strategies

<table>
<tr><th colspan="4">Emissions reduction strategies</th></tr>
<tr><td colspan="3">Travel demand and mode shift</td><td>- Taxation
- Closure of network sections
- Road pricing
- Parking control
- Decreasing speed limits
- Avoiding major new road infrastructure
- Teleworking
- Land use planning
- Traffic management
- Park and ride schemes
- Improved public transport
- Encourage walking and biking
- Public information campaigns
- Social modeling</td></tr>
<tr><td rowspan="2">Fuel type</td><td colspan="2">Conventional</td><td>- Limiting sulphur level
- Adding fuel detergents</td></tr>
<tr><td colspan="2">Alternative</td><td>- Bio fuels
- CNG
- EV</td></tr>
<tr><td rowspan="3">Fuel economy</td><td colspan="2">Fleet related</td><td>- Manufacturing restrictions
- Scrapping old cars</td></tr>
<tr><td rowspan="2">Utilisation related</td><td>Traffic management</td><td>- Congestion mitigation
- Speed management
- Traffic smoothing</td></tr>
<tr><td>Eco-driving</td><td>- Moderate acceleration
- Traffic anticipation
- Maintaining speed
- Respecting the speed limit
- Shifting gear as soon as possible
- Avoiding excessive idling
- Reduce using AC
- Closing windows at high speeds
- Taking more fuel efficient routes</td></tr>
</table>

Each of these strategies can affect the fuel consumption in different ways. Estimating the impact of different strategies on vehicle emissions is done with the aid of multiple tools. In Chapter 2 the process of emissions estimation will be discussed in detail. The emissions estimation is a very sensitive process and requires attention to details in every step. Even a minor change in any aspect can result in a significant error in the estimates and consequently a wrong policy recommendation. The objective of this study is to understand the emissions estimation thoroughly and to provide possible improvements.

1.2 Objectives

The main objective of this study, as mentioned briefly previously, is to enhance the emissions estimation methods. To achieve the main objective, three specific objectives were identified:

1- The first specific objective is to understand the GHG emissions estimation methods, and to identify the gaps and challenges. To achieve this objective, the available literature was reviewed to identify the main variables and methods for calculation. It is necessary to understand the theoretical background since the emissions models are based on them. In addition, to determine the impact of each variable on emissions and in comparison with other variables, a sensitivity analysis is conducted. Also, usually there are more than one variable that can impact the fuel consumption; therefore, in a cross analysis, the best and worst-case scenarios are offered to demonstrate the magnitude of impact of change in multiple variables at the same time.

2- The GHG emissions estimation models are usually complex and sensitive to the input data. The emissions model that is presently used in Quebec is MOVES (Motor Vehicle Emissions Simulator), one of the most sophisticated emissions models. This model is very capable yet open for improvements. The second specific objective is to understand the model, its sensitivity to the input data and to identify the most possible improvements.

3- The last and main specific objective is to evaluate and understand the local driving behaviour and to improve the methodology to construct average driving patterns. Driving patterns (i.e. driving cycles) are a key component of the emissions models, which represents the average driving behaviours in a region. Failing to provide accurate driving patterns to the emissions models can result in significant error in estimations and therefore erroneous policy recommendations.

1.3 Original contribution

Each specific objective of this study brings an original contribution to the previous studies. The first specific objective provides a good understanding of the emissions modeling and gathers all the emissions factors together, to deliver a comparative overview. The previous literature has been focused on each of the emissions factors separately and therefore, it would be difficult for practitioners to understand which factor contributes the most so that they can prioritize their decision-making.

Our second specific objective can benefit both scientists and practitioners; regarding the use of emissions model MOVES. Such models are usually used as is, without in depth analysis of its structure and its sensitivity to the input databases. In our second objective, a comparative sensitivity analysis for CO_2 emissions will be conducted. Previous studies are mainly focused on pollutions and not CO_2 emissions, since the air pollution has an instant influence on health. It is just recently that the GHG emissions have started to be controlled and observed. The pollutant emission does not depend only on vehicle activity and it is largely influenced by the emission control technology and is different for different gases. Therefore, it requires a whole new discussion that does not fit in this research. Both the sensitivity analysis of CO_2 emissions and the comparative analysis are the original contribution of this objective.

The last and the most significant contribution of this study that is covered in the last objective, is to provide an enhancement in emissions estimation methodology. The flow of this study enables us (based on the results of the previous objectives) to identify the possibilities of enhancement and to choose the most significant factor and yet achievable with the resources available. To achieve the objectives of this research a data collection is conducted to record the real-world vehicle activity. In addition, several open-source databases are used. All datasets are presented and discussed in Chapter 3.

1.4 Plan

This thesis contributes to the enhancement of the emissions estimation methodology. The first chapter, the introduction, was dedicated to the presentation of climate change and the contribution of transportation in the Greenhouse Gas emissions, as well as a brief summary of the main policies to reduce vehicles' emissions. The main objectives and the contributions of this research are also discussed in this section.

Chapter 2 is a review of the literature on emissions estimation process. It includes introduction on emissions testing as well as emissions modeling and emissions estimation packages. In this chapter we also get familiar with the concept of driving patterns and the methods for developing an average driving pattern.

Chapter 3 presents the datasets that are used in this study as well as the data collection procedure and the descriptive statistics of the recorded speed data. In Chapter 4, the impact of different variables on fuel consumption is discussed using the equations from the literature review and the real-world dataset collected for this study.

In Chapter 5, one of the most recent and capable emissions estimation packages (MOVES) is analyzed. In comparison with other emission models MOVES is able to calculate emission for different aggregation, scale and scenarios. It is very flexible for using the local data and is possible to do modifications to the input data, where as in certain models the data is already a part of the software and it leave no room for modifications. For example, In MOVES it is even possible to change the specification of fuels (a review of different emission models is provided in section 2.4). The emissions estimation models are usually very sophisticated and rely on extensive input databases. Therefore, the accuracy of these databases can influence the results significantly. In this chapter, a sensitivity analysis is conducted to evaluate the impact of each input database.

Chapter 6 reviews the available methods for driving cycle development. Driving cycles are considered as the backbone of the emissions estimation. After the review of the previous methods and the introduction of new methods, the possible enhancements are provided. The last chapter, Chapter 7, is dedicated to the overall conclusions as well as the limitations and recommendations for future studies.

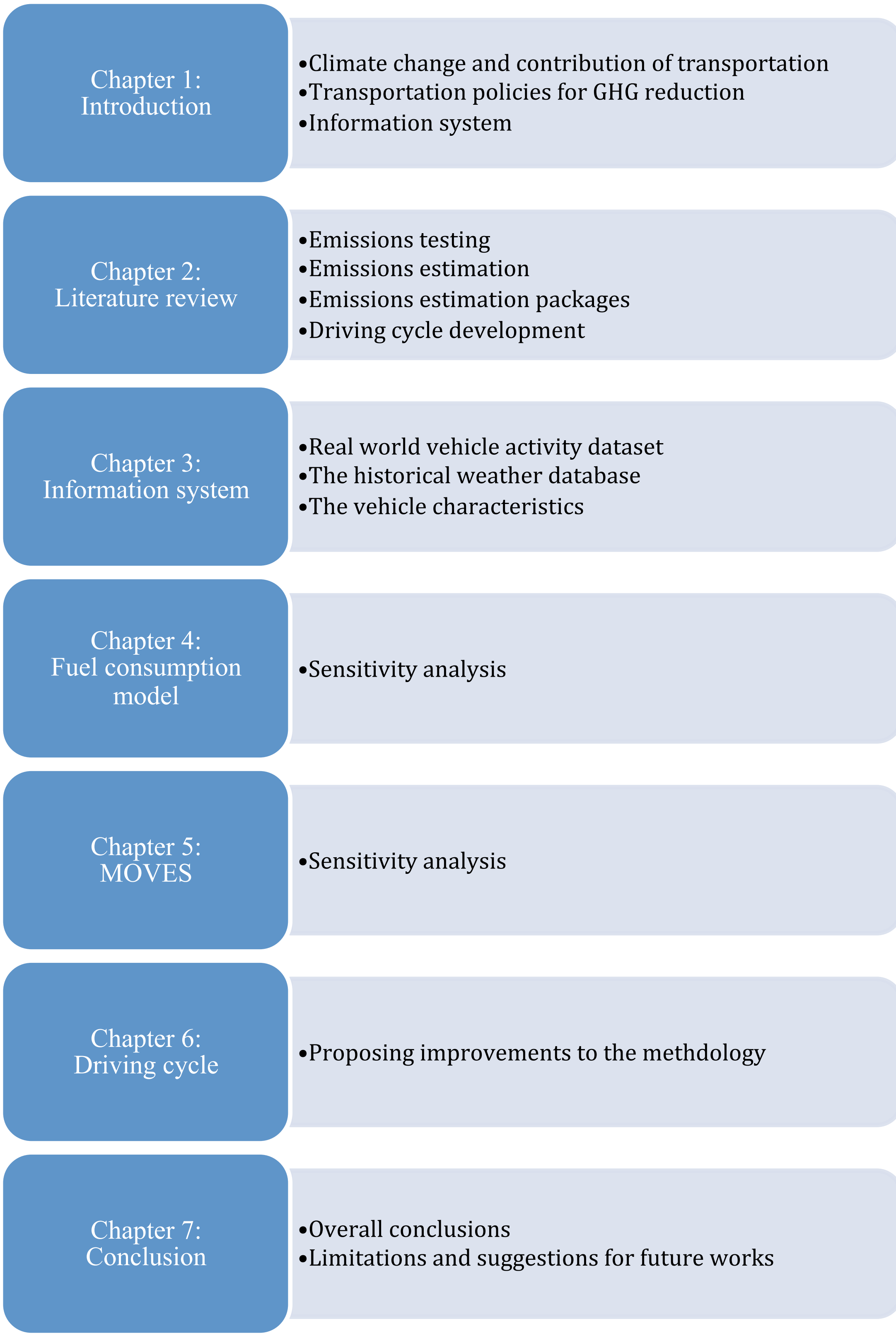

Figure 1.7: The structure of the thesis

CHAPTER 2 LITERATURE REVIEW

Why do we need to calculate emissions?

As explained in American Public Transportation Association's (APTA) *recommended practice for quantifying Greenhouse Gas emissions from transit*, there are five main reasons to estimate emissions levels in the transit context (APTA, 2009):

1- to understand the benefits of transit systems,

2- to evaluate the eligibility of new funding resources,

3- to report to carbon accounting and trading organizations,

4- to be able to set and monitor the targets in local/regional climate action plans, and

5- to support internal efforts to reduce emissions.

Therefore, the transport and environment officials, investors, and stakeholders are interested to know how transport interventions affect traffic, energy demand, and emissions. There are different methods or equipment to measure the vehicle's emissions and fuel consumption (refer to section 2.2. for a review on the main methods for measuring vehicle emissions). However, it is not yet possible to track all of the vehicles' emissions at all times; therefore, it is necessary to, as precisely as possible, estimate these emissions.

Regarding the main objective of this research, which is enhancing the emissions estimation methodology, this chapter is a review and analysis of the available methodologies and studies to identify the possible improvements, based on available resources. The emissions estimation has basically four main elements: the activity, modal structure, modal energy intensity, and carbon content of fuel (Figure 2.1).

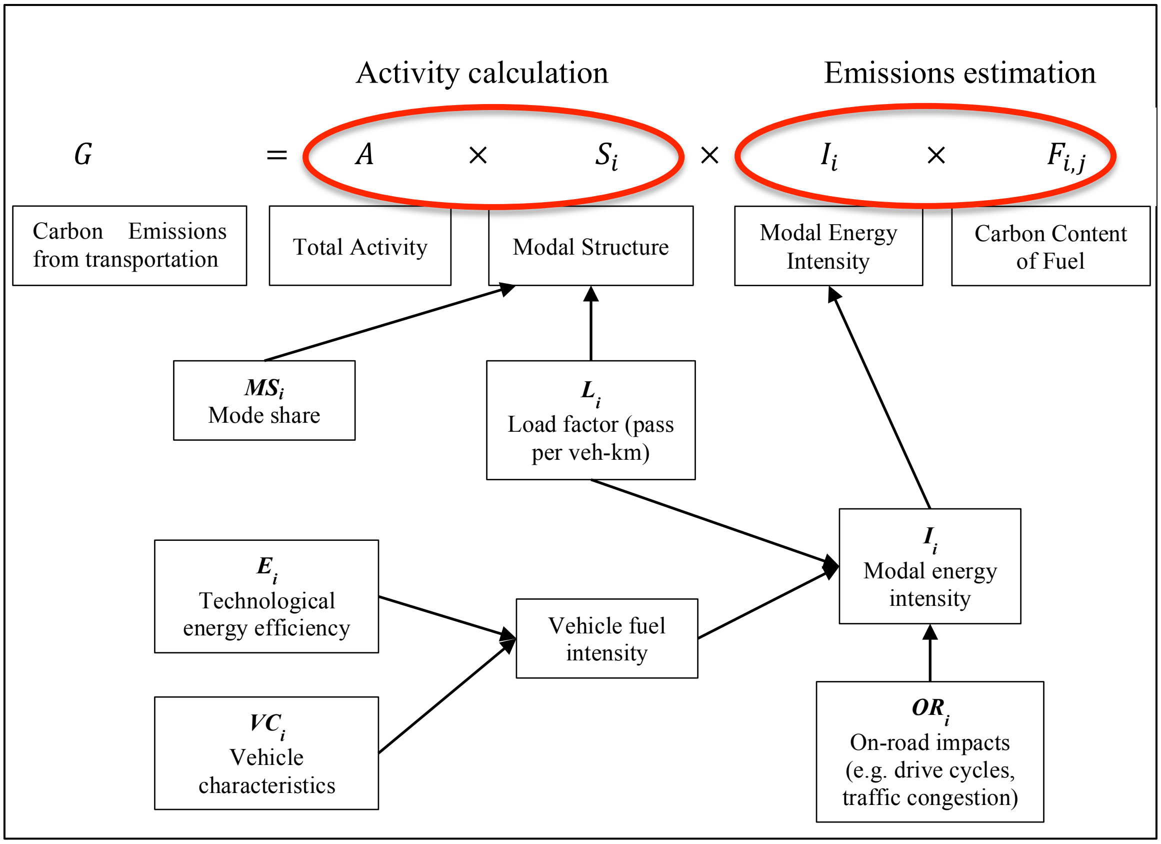

Figure 2.1: General framework for carbon emissions estimation (reproduced from: Schipper, Cordeiro, & Ng, 2007)

In a regional scale, these four elements of the emissions estimation process are usually calculated in two steps. The first step, which is the estimation of the activity and modal-share, is done using a travel demand model. The second step is to calculate modal energy intensity (e.g. how much energy is required to do a certain activity in a certain mode) and the carbon content of the fuel that is estimated by emissions models.

Based on this principal framework, the first section of the literature review is organized in two main sections: the activity calculation and the emissions estimation. Although the focus of this study is the emission estimation, it is essential to understand the role of activity calculation in emission calculation. Therefore, a brief introduction of activity calculation is provided.

This literature review is organized in four main sections: emissions testing, emissions factors, emissions models and driving cycle development. Emissions testing or the data collection in vehicle emission studies is the fundamental part of the emissions modeling. Section 2.2 provides an introduction to main emissions measurement methods, followed by a comprehensive review of the emissions modeling (section 2.3). Both, these emission models and the results of the data collections, are then used in the emissions estimation packages that are introduced in section 2.4.

Most recent emissions models take the driver's behaviour into consideration and it has been discussed that driving behaviour can have a significant influence on the fuel consumption and the vehicle emissions. The driving behaviour is usually demonstrated by the driving cycle (see the definition of a driving cycle provided in section 2.2). Driving cycles are one of the main components of emissions models; it has also been confirmed in several studies that driving cycles are different in different regions, and it is recommended for each region to have their specific local driving cycle. The available methods for the development of the driving cycles are discussed in section 2.5.

2.1 Activity calculation

As mentioned earlier, activity calculation is the first step in emissions estimations. The vehicle activity can be estimated in two scales: the macro-scale, in which the activity is calculated at a national, provincial, urban or regional level, and microscale, where the activity is calculated on a smaller section such as road links, intersections, etc. In the macroscopic scale, the activity is usually estimated with the aid of the travel forecast models; the model provides the volume and the average speed on each road section. On the other hand, in a micro-scale, the activity is calculated using the traffic microsimulation models. The micro-scale models are usually applied when more detailed activity data is required to calculate the instantaneous emissions, such as the instantaneous speed of the vehicle.

2.1.1 Macro-scale

In macro-scale, there are two main frameworks in travel demand modeling: the conventional four-step modeling and the activity-based modeling. The initial application of analytical methods in transportation modeling began in the 1950s with the introduction of the four-step modeling. As we can tell by its name, the foundation of the model is based on four steps (Figure 2.2): trip generation, trip distribution, mode choice, and route choice (McNally, 2008). Using these models, the activity can both be estimated for either links or trips. In a link-based approach, the emission factor is calculated for the volumes on roadway segments, whereas in the trip-based model, an average emissions factor is calculated on the entire trip.

It is discussed that there are significant dissimilarities between the two methods. In a comparison between the two, Bai, Chiu, and Niemeier (2007) used a dynamic traffic assignment method to generate trip-based results (for comparison of the static vs. dynamic traffic assignment refer to Chiu et al. (2011)). They discovered that the link-based approach resulted in higher emissions. Also, the link-based emissions are more sensitive to facility-related changes, while the trip-based emissions are more sensitive to demand-related changes. However, it is not clear which method produces more reliable results.

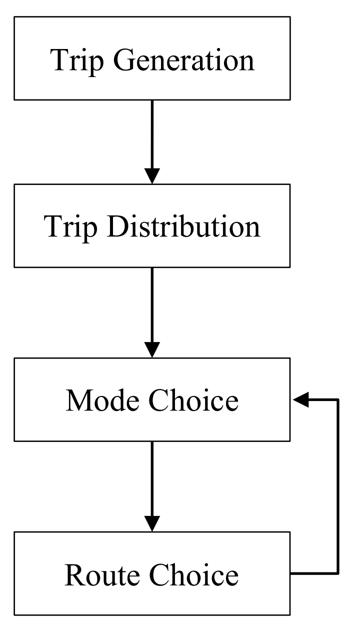

Figure 2.2: The four-step modeling framework

The other main approach in travel demand modeling is the activity-based approach (Figure 2.3). These models are based on the activity rather than the trip (for detailed information on activity based modeling you can refer to Pas (1997), and Ben-Akiva and Bowman (1998)). Regarding the emissions estimation, the activity-based models have one main advantage over the other models; they enable us to classify the emissions based on the activity type and passengers' characteristics. These findings enable policy makers to identify the most important contributors to emissions and plan accordingly (Ko, Park, Lim, & Hwang, 2011). There are several studies that used activity-based transportation models in conjunction with emissions estimation; however, we won't discuss them further, since this study is focused on emission estimation and improvement of emission estimation process (Barla, Miranda-Moreno, Savard-Duquet, Thériault, & Lee-Gosselin, 2010; Beckx, Arentze, Int panis, & Janssens, 2008; Beckx, Arentze, & Janssens, 2007; Hao, Hatzopoulou, & Miller, 2010; Hatzopoulou, Miller, & Santos, 2007; Panis, 2010; Recker & Parimi, 1999; Shiftan, 2000).

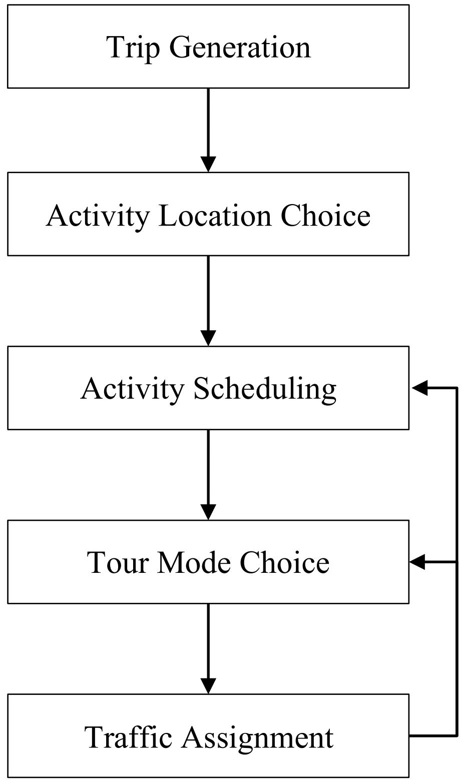

Figure 2.3: An example of the activity based model framework (Roorda & Miller, 2006)

2.1.2 Micro-scale

The macro-level models are useful to evaluate the large-scale policies as well as emissions reporting. However, it is sometimes necessary to calculate emissions on a smaller scale with more details. For example, such models cannot reflect the impact of the intersection design on emissions. For this purpose a more disaggregated information is required, such as instantaneous speed of one or multiple vehicles. That's where a microsimulation traffic model is used. For example, in a study on evaluations of traffic control strategies, Chen and Yu (2007) used VISSIM (a microscopic traffic simulation model) to evaluate the impact of a bus exclusive lane and traffic signal timing plans. These models are usually based on the traffic flow theories.

To summarize, there is no overall preference among the methods. Each method can serve a specific purpose and has its own advantages and disadvantages. For example, a link-based approach can provide a good understanding of the network and can help to identify the problematic sections. On the other hand, the activity-based approach can demonstrate which group of consumers or which activity contributes the most to GHG emissions. Also, sometimes it is necessary to use two different methods. For instance, to evaluate on the construction of a new road, as a first step a transportation forecast model is used to estimate the mode share and the volume on the link as well as the average speed. For the second step, a microscopic model can be used to determine the best design.

Also, depending on the output of the activity model the scale of the emissions model is defined. For example, having an average speed on the link, the instantaneous emissions cannot be calculated. On the other hand, using instantaneous speed to calculate the emissions in an aggregated level can increase the calculation time significantly, which is impractical. In the next section, some of the main emissions estimation equations and models will be introduced.

2.2 Emissions testing

Following the activity calculation, the second step is the emissions estimation. The emissions estimation can also be classified both at a macro-scale and a micro-scale. The final result of the estimation depends on the aggregation level of both activity model and the emissions estimation model. Before reviewing the previous research on emissions modeling, it is necessary to get familiar with the emissions measurement techniques. This section starts with an introduction on emissions testing techniques and follows by presenting factors that influence emissions levels; at the end the emissions estimation packages are introduced.

Measuring the emissions is the most fundamental part of the emissions estimation. For constructing the emissions models it is first necessary to measure the emissions under different situations and then establish the equations based on the results of the collected data. Emissions testing has been changing along with the advances in technology. There are different methods and technologies available to measure the vehicle's emissions; in this section, we avoid the technical detailing of these techniques and refrain from going past the general approaches. There are two main approaches to emissions measurement: laboratory testing and real-world measurement.

2.2.1 The laboratory dynamometer testing

Collecting data in a controlled environment is believed to provide the most reliable results. From a general perspective, the emissions testing can be either regulatory or non-regulatory. Regulatory testing is to approve if a vehicle model complies with the emissions standards. Such tests are usually conducted in emissions laboratories.

During the certification test, to measure the emissions levels, the vehicle is placed on a dynamometer in an emissions-testing laboratory. Then on a monitor a speed profile is displayed and a trained conductor follows the exact displayed speed. The speed profile is called a drive schedule or driving cycle, which represents the average driving behaviour in a region.

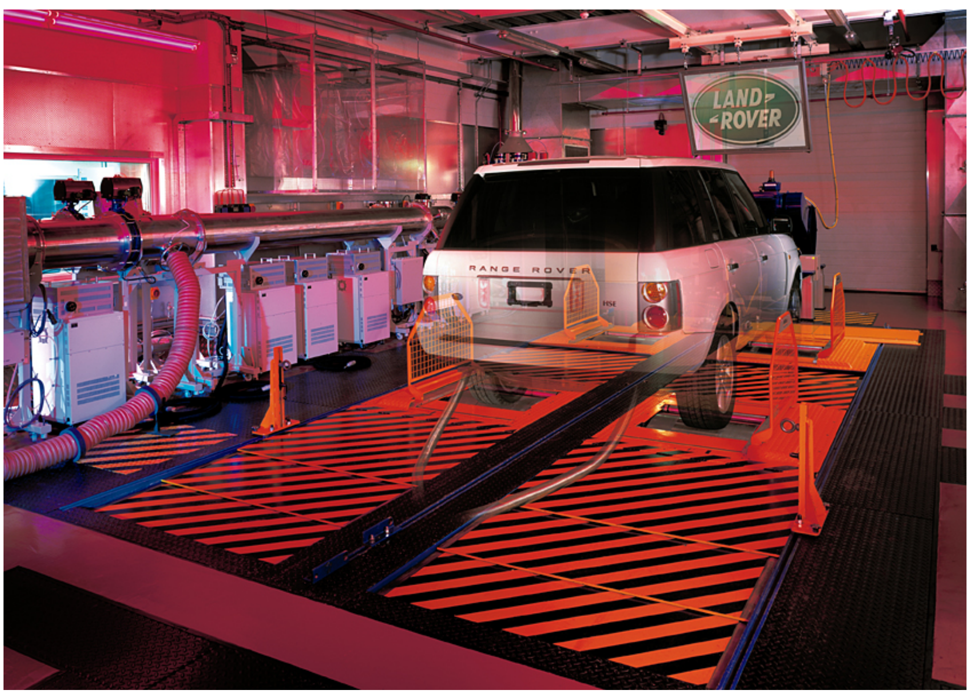

Figure 2.4: An example of the emissions testing laboratory (MERILAB, 2008)

A driving cycle indicates the speed, acceleration, and gear changes (in the case of manual transmission vehicles) during a trip. Graphically, it is demonstrated as the speed value in time (e.g. per second). One application of the driving cycles is to measure the emissions from the new vehicles to check for compliance to the standards. In Canada, until recently, a 2-cycle test procedure had been used, which represents the city and highway driving. However in 2015 a 5-cycle testing has been introduced, which covers more conditions such as cold start, air conditioning and high speed/ quick acceleration. Figure 2.5 to Figure 2.8 represent the standard driving that is used in testing for compliance by the United States and Canadian authorities. There are usually multiple driving cycles to represent different driving conditions. Table 2.1 summarizes the characteristics of each cycle.

Table 2.1: Summaries of the 2-cycle and 5-cycle tests

	5-cycle test				
	2-cycle test				
Specifications	**City**	**Highway**	**Cold temperature**	**Air conditioning**	**High speed/ quick acceleration**
Test cell temperature (°C)	20-30	20-30	-7	35	20-30
Total time (min:sec)	31:14	12:45	31:14	9:56	9:56
Distance (km)	17.8	16.5	17.8	5.8	12.9
Top speed (km/h)	90	97	90	88	129
Ave. speed (km/h)	34	78	34	35	78
Max. acceleration (km/h/s)	5.3	5.2	5.3	8.2	13.6
Number of stops	23	0	23	5	4
Idling time (% of total time)	18	0	18	19	7
Engine start	Cold	Warm	Cold	Warm	Warm

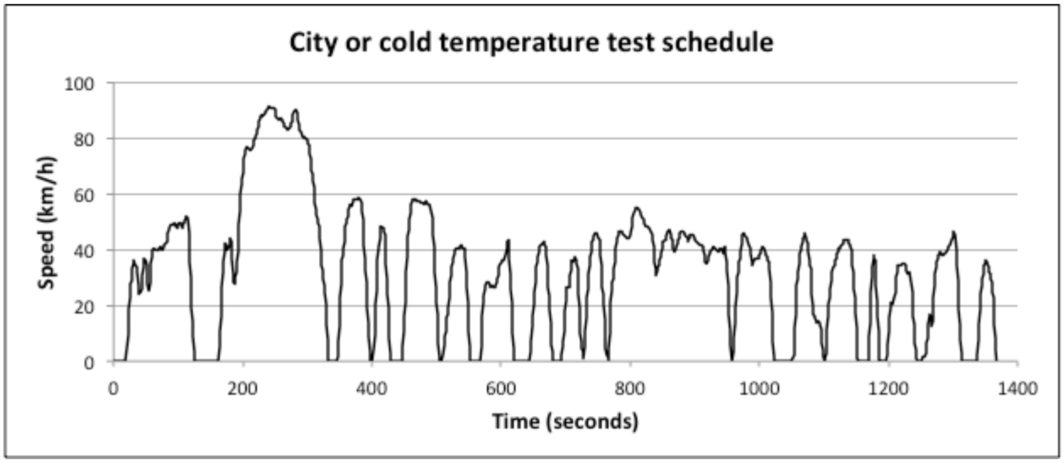

Figure 2.5: The city or the cold temperature test drive cycle (USEPA, 2015)

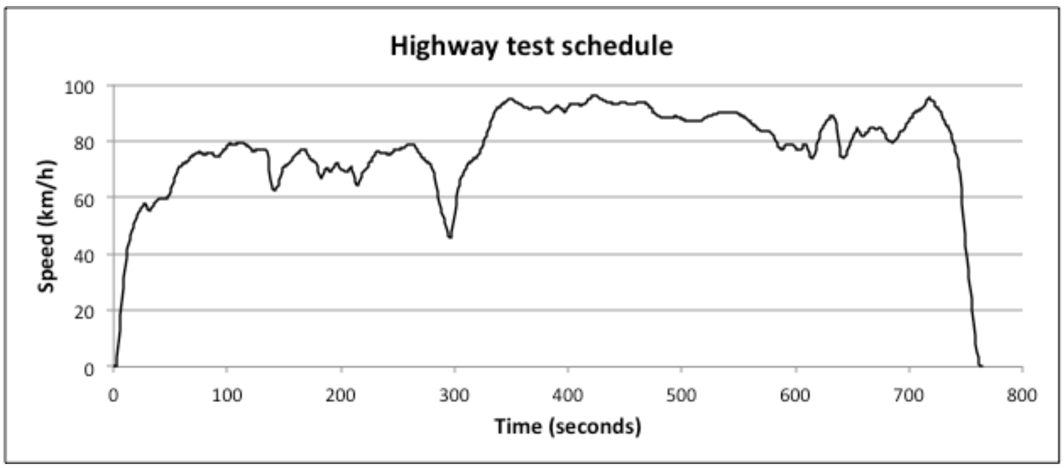

Figure 2.6: The highway test drive cycle (USEPA, 2015)

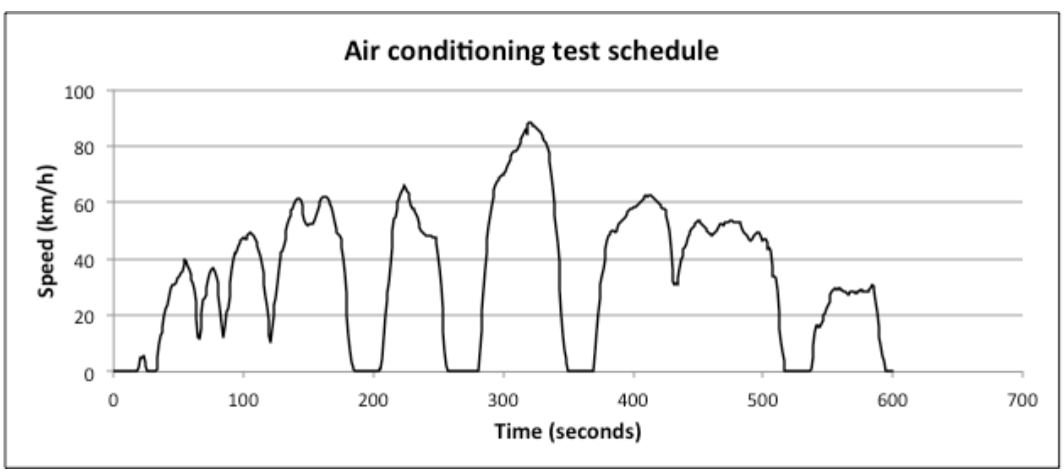

Figure 2.7: The air conditioning test drive schedule (USEPA, 2015)

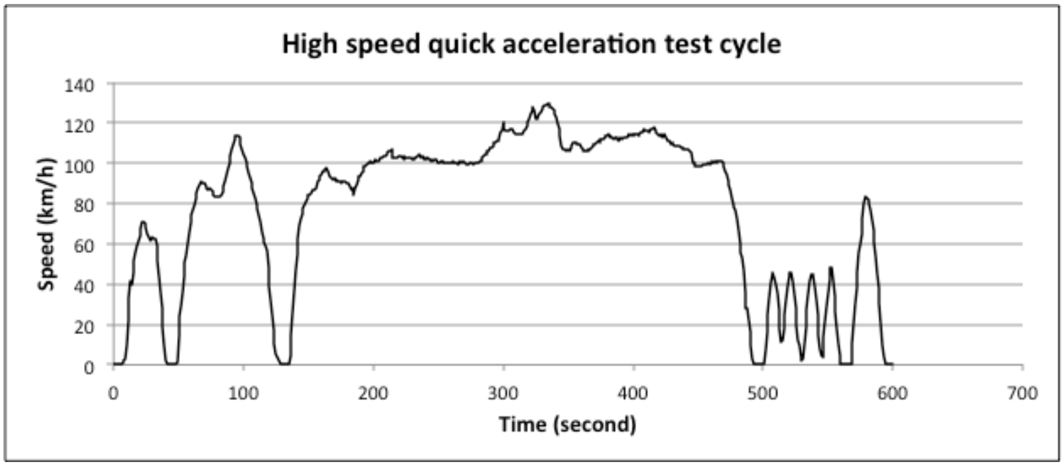

Figure 2.8: The high speed/ quick acceleration test drive cycle (USEPA, 2015)

Fuel consumption and emissions obtained in these tests are the official figures published by manufacturers. We can however hardly rely on these figures regarding fuel economy or emissions levels for every day, real-world driving. Firstly, the values provided are measured in a controlled environment, while in a real environment various factors can affect fuel consumption. Secondly, we do not necessarily drive in such precise test drive schedules and, as it is mentioned before, the speed and acceleration can have significant influence on emissions and fuel consumption. It has been discussed that the real-world driving behaviour can be significantly different from the standard test drive cycle (Pelkmans & Debal, 2006)[5].

While the controlled environment is necessary for setting national standards, for non-regulatory purposes it is strongly recommended to collect data from real world driving. In fact, the differences between the emissions measured over the certification test and those occurring during actual vehicle operation have raised important questions regarding the effectiveness of the current CO_2 reduction measures and policies (Fontaras & Dilara, 2012). As a response to this issue Portable Emissions Measurement Systems (PEMS) have been introduced.

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[5] The drive cycle and its impact on emissions estimation will be discussed in more detail in section 2.5

2.2.2 Portable Emissions Measurement Systems (PEMS)

Nowadays, thanks to advancements in technology and the advent of more reliable portable emissions measurement systems (PEMS), it is possible to measure emissions and fuel consumption in real-world vehicle use. Figure 2.9 demonstrates one of the smallest and most reliable PEMS. They can cover some of the main shortcomings of the dynamometer testing: capturing the real-world driving behaviour. Also, it is discussed that the chassis dynamometers cannot reproduce the roll inertia accurately and the real inertia might be up to five times that of the one simulated on the dynamometer (Plint & Martyr, 2001). In a comparative study of dynamometer testing and PEMS testing it is found that some vehicles with lower emissions in laboratory testing do not necessarily produce low emissions in real conditions (De Vlieger, 1997). Also, some laboratories do not provide the required facilities to measure emissions at high speeds (Farzaneh, Schneider, & Zietsman, 2010).

Figure 2.9: An example of PEMS by GlobalMRV company (GlobalMRV, 2015)

Formerly, it was believed that PEMS couldn't provide reliable measurements since they are not done in a controlled environment. However, Liu, Barth, Scora, Davis, and Lents (2010) compared the PEMS result with the laboratory results and they found that they were in excellent agreement for CO_2 and in good agreement for other pollutants such as

CO, NO_X, and HC. They also confirmed that with a good set up and proper calibration, it is possible to achieve a higher accuracy result.

Nowadays, most of the recent emissions models depend on the data collected with PEMS. However, some extra attention should be paid to collecting data with PEMS, because comparatively to the laboratory conditions, some additional factors might be introduced in a real world setting that should be carefully measured (Younglove, Scora, & Barth, 2005). Besides the laboratory dynamometer testing and using PEMS, other methods have been used in studying the vehicle emissions such as measuring the emissions in tunnels (Sjodin, Persson, Andreasson, Arlander, & Galle, 1998). However, such methods cannot provide disaggregated or instantaneous results and therefore are not suitable for instantaneous emissions modeling.

To summarize, the emissions testing or emissions measurement has two components: the technical part or the equipment for emissions measurement, and the behavioural part or driving cycle. For regulatory purposes, the controlled environment and standard driving cycles are preferred. However, for emissions modeling the more realistic condition is required, which depends on the PEMS and real-world driving. In the following sections, the main elements of the emissions estimation and main models will be introduced.

2.3 Emissions estimation fundamental

The study of emissions estimation and measuring the impact of different variables on fuel consumption and vehicle emissions was initiated in the early 80s. Ever since, the methods and technologies have been evolving at an incredible pace. However, the main concept of the instantaneous emissions estimation has not necessarily changed. In a general framework, the exhaust emissions are defined during two states of the vehicle: hot running and cold start. The hot running emissions are referred to gases produced by combustion when the engine has reached the optimum stabilised temperature, whereas cold start emissions are the excess emissions produced when the engine is colder than its optimal temperature. In this section the studies are also introduced in two main sections: the hot running emissions and the cold start emissions.

2.3.1 Hot running emissions

The main framework to calculate the instantaneous vehicle fuel consumption is to correlate it to the power required to overcome different forces. It is well known that the regular combustion engines, in general, are not very efficient; in fact, from the total energy produced in the combustion process, only around 18% is effective and the rest is lost during the power transfer. Figure 2.10 breaks down the power required for the vehicle to operate (Gyenes & Mitchell, 1994).

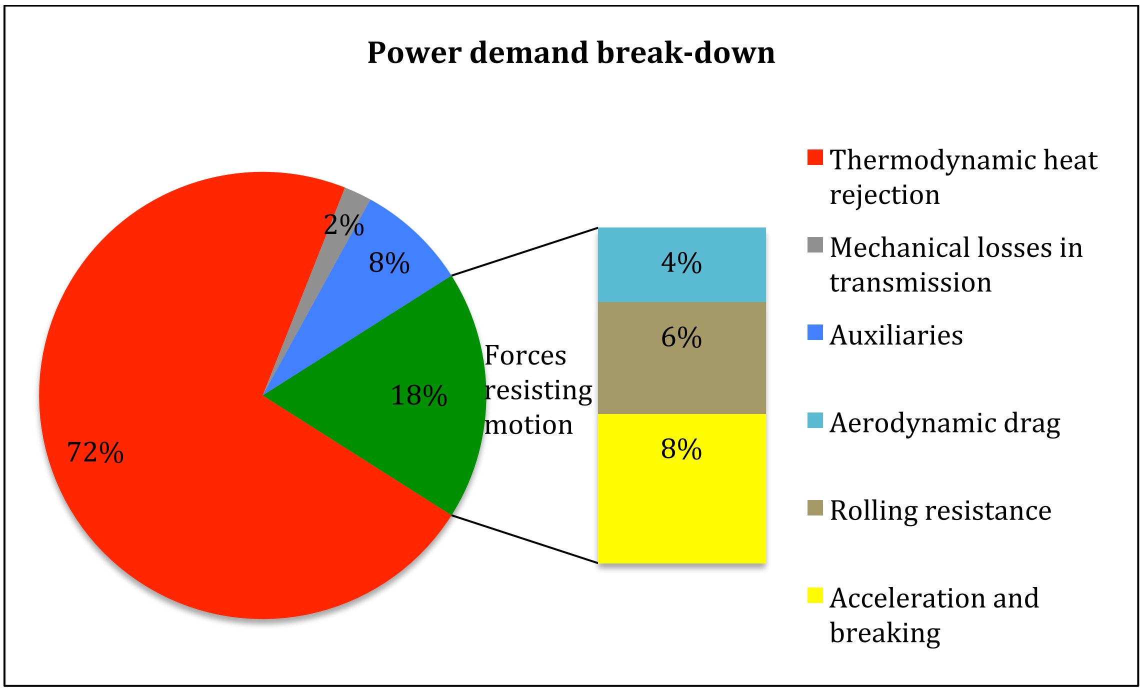

Figure 2.10: The vehicle power demand breakdown for the conventional SI engines

The general equation to relate the power demand to the fuel consumption is demonstrated in Equation 2-1 (Post, Kent, Tomlin, & Carruthers, 1984).

$$FC = \alpha + \beta P_T \qquad \text{Equation 2-1}$$

Where α is the idle fuel consumption, β is the thermal efficiency and P_T is the total power required. These two coefficients depend on the engine capacity, vehicle technology, and the power gear ratio. It is discussed that the idle fuel consumption is proportional to the Engine Capacity (EC in litres). Each litre of engine capacity equals 8.5 mL of fuel per minute in idle situation (Leung & Williams, 2000).

The other component of the vehicle emissions estimation is the estimation of the total power. The concept of the power demand for emissions estimation has been present since the early studies. As noted before, there are several forces to overcome so that the vehicle can move, the basic equation can be demonstrated in Equation 2-2 (Leung & Williams, 2000).

$$P_T = P_D + P_A + P_R + P_I + P_X \qquad \text{Equation 2-2}$$

Where P_T, P_D, P_A, P_R, P_I, and P_X are, respectively, the total power demand, drive-train resistance, aerodynamic drag, tyre rolling resistance, inertial and gravitational resistance, and auxiliary power demand (such as air conditioning). In automotive industry the drivetrain resistance, rolling resistance, and inertial and gravitational resistance are often referred to as the friction losses.

2.3.1.1 Friction losses

Among different sources of friction losses, the drivetrain resistance is the loss that happens at all times, even during idling. It accounts for about 17% of the engine power that is lost through the engine and transmission friction. The friction losses in the engine are mainly through the piston assembly, bearings, valve train, and pumping and hydraulic (Holmberg, Andersson, & Erdemir, 2012). Also, on average the energy losses in the transmission are divided into 4 subgroups: viscous loss in the oil tank, gear contact, synchronizers and bearing; friction in gear; friction in bearings, and friction in seals, forks, etc. (Tung & McMillan, 2004).

The Rolling Resistance (RR) is referred to as the "energy losses per distance traveled by the vehicle due to non-elastic deformations of the tires and losses in the wheel suspension system" (Andersen, Larsen, Fraser, Schmidt, & Dyre, 2015, p. 1). It is discussed that, depending on the vehicle speed, the rolling resistance can be responsible for 20-30% of the fuel consumption (Boere, Arteaga, Kuijpers, & Nijmeijer, 2014). There are several factors that can affect the rolling resistance:

1- the road texture,

2- the tire material properties,

3- the inflation pressure,

4- the temperature,

5- the vehicle weight,

6- the vehicle speed, and

7- the road condition.

Road texture is one of the most significant factors that define the Rolling Resistance Coefficient (RRC). The road texture is usually defined with two measures: the roughness and unevenness (International Roughness Index - IRI), and the macro texture (Mean Profile Depth - MPD). Boere et al. (2014), in a study of 30 different test tracks, found that there is a linear correlation between the texture depth and the rolling resistance coefficient. The pavements with higher depth in texture result in higher rolling resistance. In another study in Sweden, it is discussed that with reduction in MPD by 0.5 mm, the fuel consumption can be reduced by 1.1% (Hammarström, Eriksson, Karlsson, & Yahya, 2012). For instance, in the study of comparison of concrete versus asphalt (concrete having the lower MPD), Ardekani and Sumitsawan (2010), demonstrated that the emissions on concrete are lower (statistically significant).

There are extensive studies on the impact of pavement and tire interaction on fuel consumption, mostly focused on the impact of the pavement texture. Although the pavement is the most significant factor, the rest of the variables can influence fuel consumption as well. Here are some of the main findings of the studies on rolling resistance:

- Driving on gravel road can increase the fuel consumption by 29%; also, it is recommended to keep low speed to reduce the impact (Bester, 1984).
- RR increases by the increase in texture depth (Boere et al., 2014).
- RR decreases by increase in temperature (Andersen et al., 2015).
- RR increases by increase in speed (Bendtsen, 2004)
- RR decreases by keeping the tire inflated to the manufacturer's recommendation (Pearce & Hanlon, 2007).
- RR decreases by replacing the cross ply tires with radial tires (Gyenes & Mitchell, 1994).
- One pavement type that is considered more fuel efficient in one seasonal condition, is not necessarily the same in another (Taylor & Patten, 2006).

In a comprehensive analysis, the Swedish National Road and Transport Research Institute (VTI), developed a sophisticated rolling resistance model to incorporate the impact of the infrastructure on fuel consumption (Equation 2-3). Their model is based on the MPD and IRI measures on the link level (Hammarström et al., 2012; Karlsson, Hammarström, Sörensen, & Eriksson, 2011). To understand what is the range of MPD and IRI, Where, $\mathrm{F_z}$ is the normal force acting on a wheel, Cr are constant coefficients, and T is the ambient temperature.

Table 2.2 demonstrates the distribution of the road pavement measures over the road network in Sweden (Hammarström et al., 2012).

$$P_R = F_z \times (Cr_{00} + Cr_{MPD} \times MPD + Cr_{IRI} \times IRI + Cr_{IRI_v} \times IRI \times v + Cr_{Temp} \times T) \qquad \text{Equation 2-3}$$

Where, F_z is the normal force acting on a wheel, Cr are constant coefficients, and T is the ambient temperature.

Table 2.2: The percentage distribution of road texture measures

MPD (mm)	IRI (m/km)		
	0-1	1-2	2-3
0-0.5	1	1	0
0.5-1	29	33	2
1-1.5	14	16	1
1.5-2	1	1	0

Also in another micro-scale study Boere et al. (2014), considered the impact of the tire material in the rolling resistance. It is however very costly to keep updating databases to use in citywide emissions calculations. For example cracks, wears, imperfections, and even seasonal changes can modify the original data (Taylor & Patten, 2006) therefore making it difficult to use such detailed factors in the overall emissions calculation. Also to evaluate the rolling resistance precisely, we should be able to estimate what type of tire is driven on what type of road, information that is not available.

According to the studies mentioned, a smooth pavement results in lower GHG emissions. However, the cost and benefit analysis of the pavement texture and type improvement is not as simple. In a life-cycle assessment of the pavement and GHG emissions, it is discussed that improving a rough pavement on high traffic volume can reduce the life-cycle GHG emissions. However on the low volume streets, the payback time when there is a positive effect on the GHG emissions may never come (T. Wang et al., 2012). Therefore, in GHG emissions reduction from the transportation sector, it is always important to consider the life-cycle benefits rather than a simple exhaust emissions analysis.

The other category of friction losses is the inertial and gravitational power often referred as the braking losses in automotive studies. It is influenced by the motor power, rotational speed, vehicle acceleration and gravitational acceleration (Thompson, Marks, & Rhode, 2002). It is discussed that a 20% improvement in the total friction losses can result in the global CO_2 to be reduced by up to 290 million tonnes in a 5-10 years perspective (Holmberg et al., 2012).

The acceleration resistance occurs when the vehicle increases its speed. In addition to speed change, the acceleration resistance depends on the gear ratio and the vehicle weight (Emmelman & Hucho, 1998). In some studies it has been suggested to use the rotational mass instead of curb mass to calculate the acceleration resistance (Equation 2-4).

$$P_I = M \,.\, v \,.\, a \,.\, \varepsilon_i \qquad \text{Equation 2-4}$$

Where, M is the vehicle mass in kg, v is speed in km/h, and ε_i is a mass factor, which is the translational mass of the rotating components dependent on the gear: 0.25 for the first gear, 0.15 in second gear, 0.10 in third gear and 0.075 in fourth gear (Emmelman & Hucho, 1998). Also, regarding the gravitational resistance, no study was found, at the moment, which has focused on it separately; however, in most models, Equation 2-12 is used to estimate the gravitational resistance.

2.3.1.2 Aerodynamic drag

In addition to the frictions, the vehicles have to overcome the air or aerodynamic drag to move. The aerodynamic drag is considered one of the main resistances a vehicle needs to overcome to be able to move forward. It is discussed that it accounts for 80% of total road resistance[6] at 100 km/h (Hucho, 2013). The main components of the aerodynamic drag are the vehicle shape, the frontal area, the air density, the wind speed, and the vehicle speed (Jimenez-Palacios, 1999). Equation 2-5 demonstrates the general model to estimate the aerodynamic drag.

$$P_A = \frac{\rho_a}{2} \,.\, C_D \,.\, A \,.\, (v + v_w)^2 . \, v \qquad \text{Equation 2-5}$$

Where ρ_a is the air pressure, C_D the aerodynamic drag, A the frontal area v is the vehicle speed, and v_w the wind speed. There are limited studies that are actually devoted to measuring the vehicle's air resistance based on the influencing factors. It is stated that an

[6] Road resistance is the addition of the aerodynamic resistance and the rolling resistance.

accurate theoretical prediction is not yet possible (Sovran, 2012). For instance, it is believed, by experience, that the open window during high speed driving increases the fuel consumption (CAA Quebec; J. Lee, 2009); however, no scientific proof is available.

2.3.1.3 Auxiliaries

The last category of the vehicle power demand consists of the auxiliaries. The term auxiliary means anything that provides additional support. In vehicular transportation, anything additional to the power required for moving or in overcoming resistance is considered an auxiliary, such as air conditioning, lights, electric heaters, windshield wipers, etc. The auxiliaries draw power from the engine and therefore, contribute to the fuel consumption. One of the most important, in regards to fuel consumption, is air conditioning. From the early appearance of air conditioning (AC), its significant impact on fuel consumption has been recognized (Barbusse, Clodic, & Roumégoux, 1998). Mobile air conditioning is considered as the second largest energy consumer after the driving process itself (M. F. Weilenmann, Alvarez, & Keller, 2010). The operation of the AC system can decrease the vehicle fuel economy by up to almost half (Welstand, Haskew, Gunst, & Bevilacqua, 2003).

To understand the significance and the determining factor, Johnson (2002) conducted a thermal comfort analysis to estimate the probability of the use of AC. He demonstrated that with a 50% reduction in AC use, 13.5 billion liters of fuel could be saved, which is equal to 5% of the total crude oil import in the U.S. Both drivers and vehicle manufacturers can help reduce the magnitude. For instance, regarding the manufacturers, an optimised AC system, advanced window glazing and localized cooling are some possible ways to do this (Johnson, 2002). Also, the users can contribute by limiting their use. The primary energy source of the AC is supplied by two mechanisms: the power to the compressor and the power for fan systems (Clodic et al., 2005). There are different AC technologies; in the most common that works with the conventional powertrain, the internal combustion engine propels the AC compressor mechanically (Rijkeboer, Gense, & Vermeulen, 2002).

To calculate the load required for AC, Fayazbakhsh and Bahrami (2013), provided a comprehensive review of the previous model as well as a new model based on the Heat Balance Method, which identifies different loads:

$$\dot{Q}_{Tot} = \dot{Q}_{Met} + \dot{Q}_{Dir} + \dot{Q}_{Dif} + \dot{Q}_{Ref} + \dot{Q}_{Amb} + \dot{Q}_{Exh} + \dot{Q}_{Eng} + \dot{Q}_{Ven} + \dot{Q}_{AC} \qquad \text{Equation 2-6}$$

Where, the $\dot{Q}$ s represent different thermal energies per unit time in W, $\dot{Q}_{Tot}$ being total thermal, $\dot{Q}_{Met}$ metabolic load, $\dot{Q}_{Dir}$, $\dot{Q}_{Dif}$, and $\dot{Q}_{Ref}$ are the direct, diffuse, and reflected radiation loads, respectively. $\dot{Q}_{Amb}$is the ambient load $\dot{Q}_{Exh}$and $\dot{Q}_{Eng}$ are the exhaust and engine load. $\dot{Q}_{Ven}$ is the load generated due to ventilation, and $\dot{Q}_{AC}$ is the thermal load created by the AC cycle. Therefore, the AC load can be calculated using the Equation 2-7.

$$Q_{AC} = -\left(\dot{Q}_{Met} + \dot{Q}_{Dir} + \dot{Q}_{Dif} + \dot{Q}_{Ref} + \dot{Q}_{Amb} + \dot{Q}_{Exh} + \dot{Q}_{Eng} + \dot{Q}_{Ven}\right) - (m_a\, c_a + DTM)\left(T_i - T_{comf}\right)/t_c \qquad \text{Equation 2-7}$$

Where T_{comf} is the target temperature (°C), t_c is a pull-down constant which is the time required for the cabin temperature to reach the comfort zone (s), m_a being the cabin air mass (kg) and c_a is the air specific heat (J/kg K). This method is a high-precision model, which considers all the possible factors[7]. However, estimating the extra fuel consumption using such models is impractical because of either the complication of such models and unavailability of the input data. Therefore, some studies tried to correlate the extra fuel consumption to more accessible inputs.

For instance, M. F. Weilenmann, Vasic, Stettler, and Novak (2005), developed a model based on 6 different situations: Urban, rural and highway for both shade and sun

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[7] It is also discussed that the speed can affect the extra fuel consumption of the vehicle due to AC, which, Roujol and Joumard (2009) found that correlation insignificant.

conditions. Equation 2-8, is the model they provided with a, b, and c being the parameters for each situations and T the ambient temperature in ^{o}C.

$$if\ T > 5°\mathrm{C}, then\ (if\ c > a.T + b, then\ emission = c, else\ emission = a.T + b)\ else\ emission = 0 \qquad \text{Equation 2-8}$$

The a, b, and c parameters are retrievable from Table 2.3.

Table 2.3: Parameters to calculate the extra CO_2 emissions or Fuel consumption from the AC

		Shade			Sun		
	Parameter	Urban	Rural	Highway	Urban	Rural	Highway
CO_2	a	2.4422	0.8522	0.6842	2.6889	0.9863	0.7778
	b	-18.7718	-9.9298	-10.9286	-17.1977	-11.2158	-12.1216
	c	18.4666	6.2840	3.6224	23.7000	5.0084	2.1753
Fuel consumption	a	0.7804	0.2847	0.2793	0.8488	0.3231	0.2790
	b	-6.0888	-3.5017	-5.0211	-5.3366	-3.7406	-4.3917
	c	5.7801	2.0163	1.1428	7.4062	1.5853	0.6512

In this research the authors assumed that the AC is always on during the warm weather since there is no data available to evaluate the probability models of AC use. They also found that the extra CO_2 emissions are not zero in 13°C but 2.4 - 18 g/km due to the demisting activity which is not considered in the U.S. model. Regarding the demisting activity they also include that “Without proof, it is assumed that this demisting activity is active down to about 4 °C, where the A/Cs have to switch off to avoid internal freezing”. Furthermore, the effect of humidity is considered in relation to the temperature. The result of the model is demonstrated in Figure 2.11.

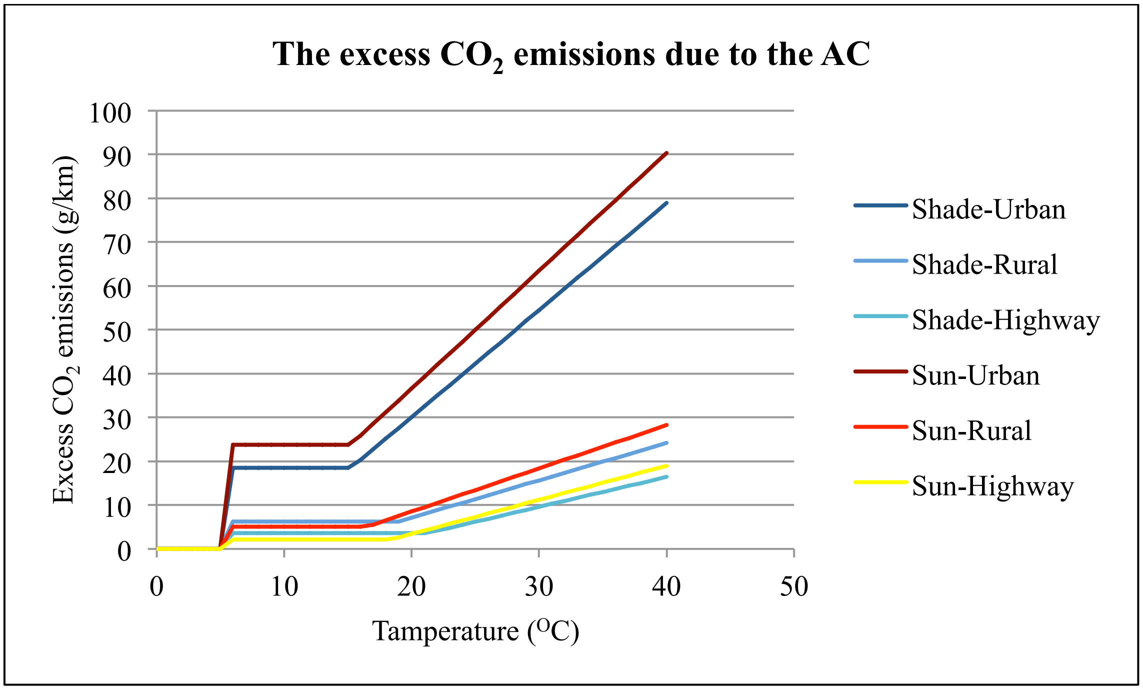

Figure 2.11: The excess CO_2 emissions due to the AC

In a similar effort in the U.S., the air conditioning impact is modeled as a part of the MOBILE6 model (Koupal, 2001). In their method they also considered the solar loads, cloud cover, soak duration, trip duration, average speed, and idle fraction in addition to the temperature and humidity. Based on these variables they proposed modeling the emissions based on the demand factor. In this method demand factor is basically the fraction of the time that the compressor is engaged which will be then multiplied by the emissions factor. Because of the difficulties in calculating the power required by AC and including in the power demand model, it is usually calculated separately as the excess emissions or fuel consumption.

An in-vehicle air conditioning system is often a sales option on the basic version of a certain type of car. An auxiliary heating system on the other hand became a standard feature on passenger cars in some countries. For interior heating the usual system the heat is drawn from is the engine's coolant. But the trend on the engine's increasing energy efficiency enforces other systems to be applied. With the increasing efficiency of the engine, too little wasted heat from the engine's coolant is available for use in the heating system, especially in the warm-up phase. Nowadays some variations on the conventional heating system are known. Some of these work electrically and draw their operating energy from the low voltage battery and the generator and thus indirectly from the engine. Others use fuel stored in the vehicle's tank for a fuel-fired heater. It is clear that these systems influence both the fuel consumption and the emissions (Rijkeboer et al., 2002). However, no relevant information was found in the literature at this moment.

In addition, nowadays vehicles come with more and more options such as steering wheel and windshield heating, powered sunroof, built-in GPS, Wi-Fi, etc. Lutsey, Brodrick, Sperling, and Dwyer (2003) identified the power requirements of some of the main accessories. However, the study was published in 2003 and since then vehicle accessories have evolved even further.

As briefly mentioned earlier, the study of the power demand can be classified in two categories regarding their scale and their approaches. In a very small scale, which is mainly the vehicle design approach, the power demand or fuel consumption is attributed to detailed calculations specific for each vehicle. Whereas on a relatively larger scale that concerns the vehicle activity in an urban context, such detailed calculations are not practical. Firstly, because it requires detailed input for each vehicle and even in case of availability it requires a vast quantity of both time and energy. But also, more importantly, we need to acquire the information on vehicle activity, environmental conditions, and driver behaviour at all times, something that is not possible at the moment. Therefore, the models that are used to estimate in an urban context are simplified, correlated with available data. However, the basic understanding of detailed power demand is necessary to be able to make the decision in making the right compromises during the simplification process. Some of the main studies in fuel consumption using the power demand methodology are discussed in the following section.

2.3.1.4 Other factors

There are other factors that can also affect emissions fuel consumption such as the transmission technology. There are several transmission technologies; among those are the manual and the automatic are the most popular. Moawad and Rousseau (2014), in their comparison of transmission technologies, demonstrated that the automatic transmission can improve fuel consumption for all passenger vehicle categories. The benefits range from 5.5% in mid-size SUV (Sport Utility Vehicle) to 11% for compact cars. Different studies have analyzed different methods for improving the transmission efficiency by enhancing the automatic shifting algorithm such as a study by Ngo, Hofman, Steinbuch, Serrarens, and Merkx (2010). It is discussed that an overall 1.5% improvement in transmission efficiency can result in a 0.1 km/L increase in fuel economy (Nam & Giannelli, 2005). Regarding transmission technology, it is commonly believed that older vehicles are less efficient because of the wearing down of their transmission system or the build-up deposit on the cylinder walls and head; however, such claims have not been scientifically proven (P. Boulter, 2009; P. Boulter et al., 2009; Ntziachristos & Samaras, 2000). It is interesting to incorporate such factors in emissions estimations to develop more flexible and comprehensive models. However, with a good sample, the more recent emissions models with updated coefficients do reflect the impact of such factors. Therefore, it is recommended to update the emissions factors regularly to have more reliable estimates.

2.3.1.5 Total power demand

The concept of power demand for emissions estimation goes back as early as the 70s. In one of the first studies available, Ford Co., LaPointe (1973) correlated the positive work to the fuel economy, in an aggregated approach, for an entire trip. Where the positive work is defined as the total power required for overcoming inertial, rolling friction and aerodynamic forces. At around the same time in Australia, H. C. Watson, Milkins, and Marshall (1979) also worked on simulating the exhaust emissions mainly for aggregated results. However, they noted that the model has some flaws for estimating at an instantaneous rate, due to the over-estimation of the deceleration and the underestimation of the acceleration rates. They later solved the problem by identifying two states of the engine: throttle open and throttle close, and provided an equation to interpret the state of the throttle (H. C. Watson, Milkins, Holyoake, Khatib, & Kumar, 1985).

During the same period, also in Australia, another group of researchers was working on the power demand concept. The studies by Post et al. (1984) are among the most cited early studies of fuel consumption estimation. In their analysis they offered a more in depth and detailed approach for estimating the instantaneous power demand. However their methodology was later criticized by Akçelik and Biggs (1985), the results providing the total fuel consumption for a trip and therefore not suitable for instantaneous analysis. The model was then improved by Bowyer, Akçelik, and Biggs (1985) using both on-road and dynamometer testing to calibrate the model and was also revised recently (Akçelik, Smit, & Besley, 2014). Among all the models presented in different studies, the one in Leung and Williams (2000) (Original research from Richardson (1982)) provides the most comprehensive and detailed instantaneous model. Equation 2-9 to Equation 2-12 demonstrate their model for each power component.

$$P_D = 2.36\times10^{-7} v^2 M \qquad \text{Equation 2-9}$$

$$P_R = (3.72\times10^{-5} v + 3.09\times10^{-8} v^2) M \qquad \text{Equation 2-10}$$

$$P_A = 1.29\times10^{-5} C_{\text{d}} \text{A}\, v^3 \qquad \text{Equation 2-11}$$

$$P_I = 2.78\times10^{-4} (a + g \sin\theta)\, M\, v \qquad \text{Equation 2-12}$$

Where,

P_D = Drivetrain resistance (kW),

P_R = Rolling resistance (kW),

P_A = Aerodynamic resistance (kW),

P_G = Inertial and gravitational resistance (kW),

M = Vehicle mass (kg) including occupants and other loads,

v = Instantaneous speed (km/h),

a = Instantaneous acceleration (m/s^2),

C_d = Aerodynamic drag coefficient,

A = Frontal area (m^2),

θ = Road gradient,

g = Gravitational acceleration

Based on the power demand model some other variations have also been introduced. For example, it is discussed that the ratio of the vehicle power to mass can provide a good parameter for estimating the emissions (P_T/M_v). This ratio is referred to as the Vehicle Specific Power (VSP or SP) and was first introduced by Jimenez-Palacios (1999). The author noted that the concept was inspired by the positive kinetic energy method initially developed by H. C. Watson, Milkins, Preston, Chittleborough, and Alimoradian (1983). This factor has been widely used in vehicle emissions estimations ever since (Coelho, Farias, & Rouphail, 2006; Frey, Zhang, & Rouphail, 2008, 2010; Kean, Harley, & Kendall, 2003; Nesamani, 2010; Song & Yu, 2009; H. Wang, Fu, Zhou, & Li, 2008; Younglove et al., 2005). The VSP concept has been used in some recent emissions models such as MOVES, IVE and EMFAC. Equation 2-13 provides the VSP equation using typical values for rolling resistance and drag coefficient (Jimenez-Palacios, 1999).

$$VSP = v.(1.1\,.\,a + 9.81\,.\,G + 0.132) + 3.02\,.\,10^{-4}.(v + v_w)^2.v \qquad \text{Equation 2-13}$$

In this case VSP is the specific power in kW/metric Ton or W/kg or m^2/s^3 and v_w is the wind speed. The vehicle emissions are then calculated from the VSP look-up tables (Appendix A). The simplified equations can be very helpful specifically when the detailed variables are not available for all the vehicles. It should also be taken into consideration that the parameters depend significantly on the fleet, climate, and the network.

Table 2.4 provides a summary of the accessible literatures that contributed to and applied the power demand model in their analysis, in chronological order.

Table 2.4: A summary of the main literature modeling the power demand

	Notes	Aggregation	Also used by:
LaPointe (1973)	Quantifying the most contributing factors for the decline in fuel economy.	Total power per cycle	
H. C. Watson et al. (1979)	A more simplified power model.	Km	Akçelik (1983)
(Sovran & Bonn, 1981)	Introduction of the detailed power demand or road load model in its current form (Cited in: Nam & Giannelli, 2005)		
(Post et al., 1984)	The model is developed to calculate the instantaneous fuel consumption. However, it has been criticised that the results provide the total fuel consumption for a trip and therefore not suitable for instantaneous analysis (Akçelik & Biggs, 1985).	Minute	(Leung & Williams, 2000)
(Bowyer et al., 1985)	Instantaneous fuel consumption model	Minute Kilometer	(Biggs & Akçelik, 1986) (Prahara, S. Lubis, & Sjafruddin, 1999) (Akçelik et al., 2014)
(Redsell, Lucas, & Ashford, 1993)	One of the first studies that used the PEMS to measure emissions and the model is based on the real driving condition.	Kilometer	
(Barth et al., 2000)	The development of the Comprehensive Modal Emissions Model	Mode	(Rakha, Ahn, Moran, Saerens, & Van den Bulck, 2011) (Cappiello, 2002) (Cappiello, Chabini, Nam, Lue, & Abou Zeid, 2002)

In addition to the power demand models, there are some other studies that used a simpler regression models to calculate the fuel consumption or the exhaust emissions. For instance, in Evans and Herman (1976) the vehicle speed is correlated to the fuel consumption. This simple regression model is a distance-based model. The relation between speed and fuel consumption per unit of distance is a U-shaped relationship, where the optimum speed range is between 60 and 90 km/h (El-Shawarby, Ahn, & Rakha, 2005).

However, it was noticed in the measurements that the same average speed can result in different fuel consumption rate, on which acceleration plays an important role. Therefore, later on other scientists tried to improve the simplified method by integrating the acceleration in the model (Ahn, Rakha, Trani, & Van Aerde, 2002; André & Rapone, 2009; Jost, 1992; Joumard, Jost, Hickman, & Hassel, 1995). To go further, in another study, the idle time was also incorporated within the model (C. Lee & Miller, 2001). Also, in a study of the vehicle inspection/maintenance, the characteristics of the vehicles were correlated with their emissions to identify the more pollutant vehicles (Washburn, Seet, & Mannering, 2001). The simple models can sometimes provide good results and specifically useful in the shortage of data. However, they are dependent on the fleet composition, geographical changes, network characteristics and the driving habits.

2.3.2 Cold start

As mentioned in the beginning of this section, the second category is the cold start. The excess emissions from the cold start is mainly due to the increased friction when the engine components and the oil are at low temperatures in complete combustion and with the catalyst inefficiency (Bielaczyc, Szczotka, & Woodburn, 2011; P. Boulter & Latham, 2009). It is believed that in cold temperatures the excess emissions can be significant. As part of the ARTEMIS[8] project, in Europe, André and Joumard (2005) developed a model to estimate excess emissions produced by the cold start. The model calculates the excess emissions per trip.

$$EE(T,V,\delta,t) = \omega_{20°\mathrm{C},20km/h}.\, f(T,V).\left\{\frac{1-e^{a.\delta}}{1-e^{a}}\right\}.\, g(t) \qquad \text{Equation 2-14}$$

Where,

EE	=	Excess emissions for a trip in g
T	=	Ambient temperature in °C
V	=	Mean speed in km/h during the cold period
$\delta = \dfrac{d}{d_c(T,V)}$	=	Dimensionless travelled distance

[8] Assessment and Reliability of Transport Emissions Models and Inventory Systems

d	=	Travelled distance
$d_c(T,V)$	=	Cold distance (Appendix A- Table 4)
t	=	Parking time
$\omega_{20°C,20km/h}$	=	A coefficient corresponding to excess emissions at 20°C and 20 km/h
$f(T,V)$	=	Correction coefficient (Appendix A- Table 2)
a	=	Coefficient to calculate the cold distance (Appendix A, Table 3)
$g(t)$	=	The impact of parking time (Appendix A, Table 5)

This is one of the most comprehensive models that has been used in several other studies (M. Weilenmann, Favez, & Alvarez, 2009).

In this section we discussed different models calculating emissions, using sets of variables or situations. Reviewing the previous studies revealed that some aspects of emissions estimations still require extra attention. For example, regarding the fact that AC can have a significant impact on vehicle emissions and the uncertainty in AC use, more studies are required. Also, regarding the aerodynamic resistance of the vehicle, the variables lack more precision in small-scale analysis, such as the impact of the open window or extra accessories on the vehicle exterior. To determine how different variables can contribute to the total fuel consumption or emissions, a sensitivity analysis is conducted in Chapter 4; also, the main strengths and gaps in emissions estimations will be discussed further. As mentioned previously, emissions estimation is a sensitive process and using such equations can become overwhelming to the practitioners as well as increase the possibility of errors. Therefore, such models are usually gathered to establish comprehensive emissions estimation packages.

2.4 Emissions estimation packages

In the previous chapter we became familiar with elements of emissions estimation and some of the main concepts of emissions modeling. These models are usually collected in software packages to make it easy for the users. There are various emissions packages used in different regions, each of them having its own specifications, capabilities and shortcomings. In this section a review of some of the main emissions models is provided. Regarding their approaches, the emissions models are usually classified in six categories (P. G. Boulter, McCrae, & Barlow, 2007; Smit, Ntziachristos, & Boulter, 2010):

1- Aggregated emissions factor models

2- Average speed models

3- Traffic situation models

4- Traffic variable models

5- Cycle variable models

6- Modal models

The aggregated emissions factor models are the simplest models. They are basically simple lookup tables, which provide the average fuel consumption or emissions values for each pollutant type per Vehicle Kilometers Traveled (VKT). These values are also different for different road type and vehicle type. These models are usually based on the national inventory values. The detail can vary from a national average level to separate values for each vehicle type and road type. The advantage of these models is the simple process of emissions calculation. However, the estimates are very rough and do not reflect the influence of changes in any factors other than VKT or vehicle type.

The average speed models are very similar to the aggregated emissions models. These models provide a more complex lookup table with a specific value for each speed range. The output of these models is usually stated in grams or litre per vehicle kilometer. The average speed approach is one of the oldest models available and has been widely used until recently. The advantage of these models over the aggregated emissions factor is that they can reflect the impact of speed variations along a road section on emissions. However, the problem is that different speed profiles can return same average speed but result in different emissions levels (P. Boulter et al., 2009).

The traffic situation approach was an effort to improve the average speed models by incorporating the acceleration profiles in the modeling structure. For this purpose, different traffic situations were taken into consideration. The definition of traffic situation can be different for different models but they usually represent different driving behaviours such as stop and go, aggressive, free flow, etc. The problem of such models is that traffic situations are defined by the operators and can be influenced by their judgement.

Traffic variable models have quite a different approach comparatively to the previous models. These models incorporate some traffic flow properties to the model such as traffic density, queue length and signal setting. These models eliminate the impact of the objectivity of the operators.

The cycle variable models are similar to the traffic situation approach but with a greater focus on the vehicle's operation characteristics such as idle time, average speed and positive kinetic energy. For each situation a specific driving cycle is available to represent the characteristics of the trip. These models usually require fine data, which is acquired from microscopic traffic models or Global Positioning System (GPS) equipment.

The Modal approach, which is the more recent methods of emissions modeling, is based on the operational characteristics of the vehicles. It is very similar to the variable cycle method and requires high-resolution input data. The modal models can be classified in two categories: the simple model, which consists of a lower number of modes such as acceleration, deceleration, idle, cruise, etc.; and the instantaneous models that calculate emissions and which is usually calculated based on the engine power requirement.

The instantaneous models have certain advantages over the rest of the methods. They enable us to calculate the emissions for any operational condition and any speed profile without conducting further testing. They can also provide detailed emissions estimations spatially that can improve the air quality assessment. However, it is believed that some marginal errors should be taken into consideration since the results of the data collection always include some delays. Therefore, it is difficult to allocate a specific operating condition (Ajtay & Weilenmann, 2004). It is thus suggested that such models stay limited to the research community (P. G. Boulter et al., 2007). In the following section some of the main emissions estimation packages are introduced.

2.4.1 MOVES

Motor Vehicle Emissions Simulator (MOVES) is an emissions model developed by the United States Environmental Protection Agency's (USEPA) Office of Transportation and Air Quality (OTAQ). It can calculate emissions from on-road sources as well as off-road (aerial, rail, and maritime). The model is able to estimate the emissions on four different scales: national, county, region and project. The model can return the results as inventory or emissions factor. The users can also choose between different vehicle types, time periods, geographical areas, pollutants, vehicle operating characteristics, and road types for estimation. Figure 2.12 demonstrates the main Graphical User Interface (GUI) of the model.

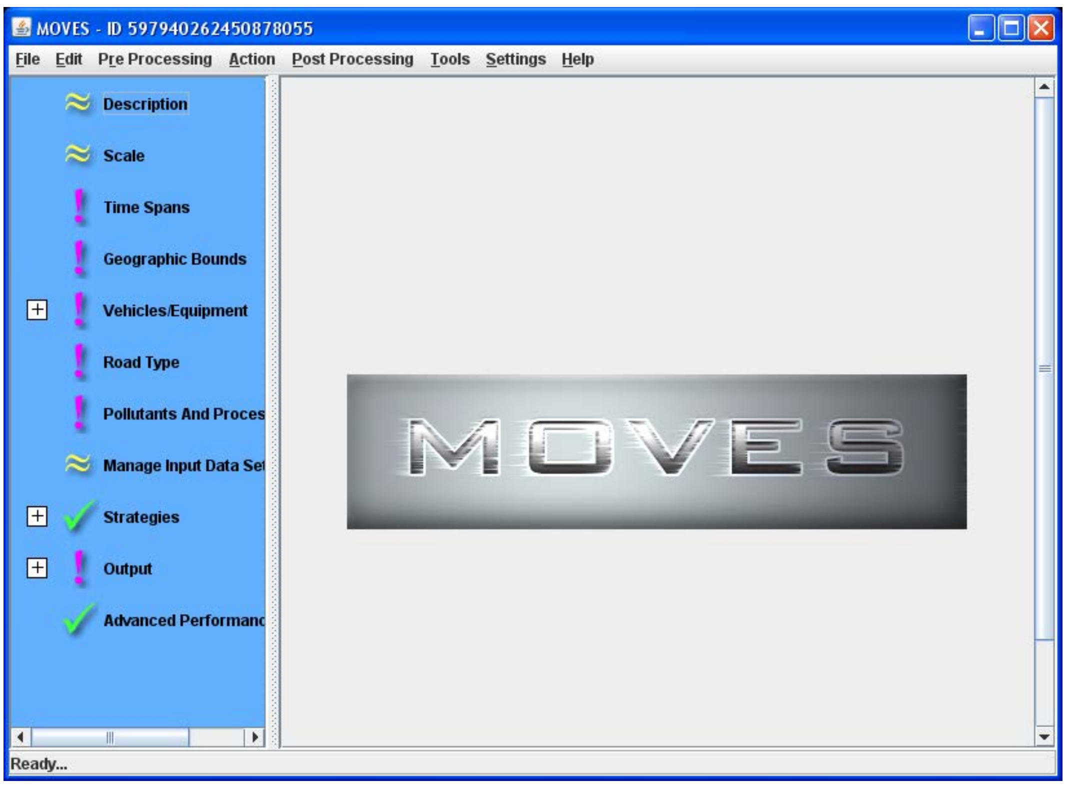

Figure 2.12: MOVES2014 Graphical User Interface

MOVES is the replacement for MOBILE, which was an average speed emissions model. The first version of MOVES was released in 2010 and has been updated regularly ever since. The current version is MOVES2014. The model requires extensive databases as input, which includes the vehicle activity, fuel, weather condition, etc. There is a default database incorporated within the package for the United States; however, it is strongly recommended that local authorities develop and use their own datasets for more precision. The users' datasets can be imported through a data manager panel, which is available for the county and project scales. Figure 2.13 demonstrates the input data required in the county data manager. The main datasets are:

- Number of vehicles for each vehicle type;
- Annual vehicle miles traveled (VMT) and its monthly, daily, and hourly distribution for different vehicle types;
- The details of the inspection/maintenance program;
- Fuel composition and the proportion of different fuel used;
- The average hourly temperature and humidity throughout the months;
- The ramp fraction or the proportion of the time vehicle spend on ramps;
- The distribution of VMT on different road types for each vehicle type;
- The distribution of vehicle ages for different vehicle classes;
- The hourly average speed distribution for different vehicle types and road types.

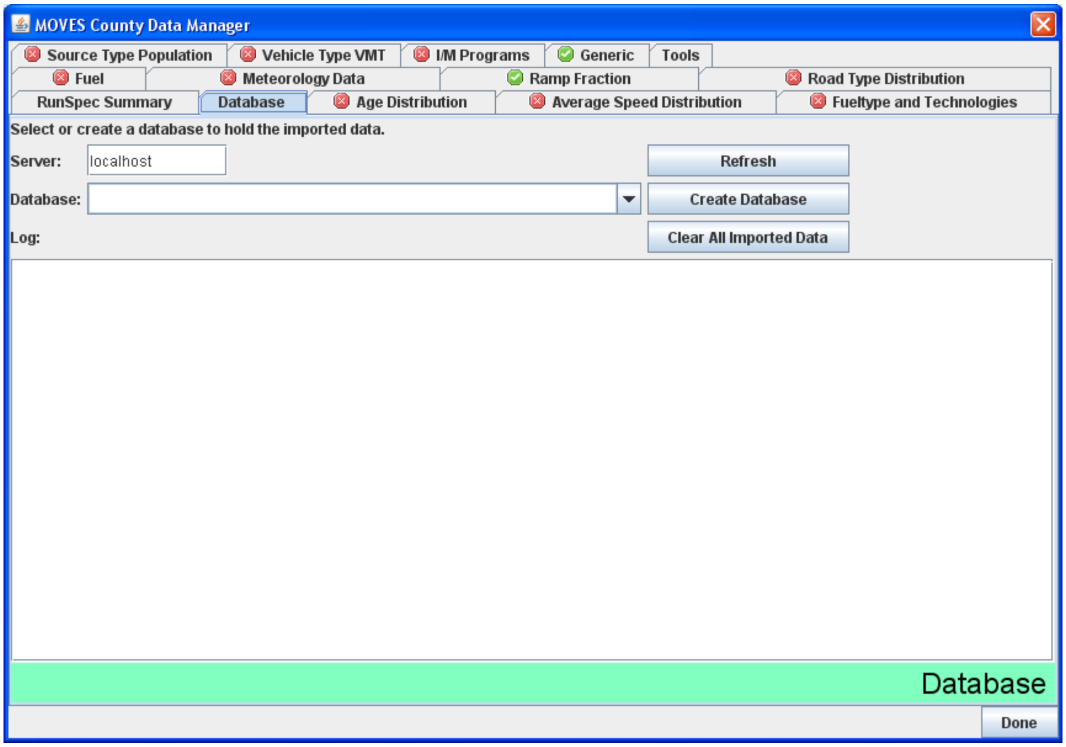

Figure 2.13: Data importer for county level

The emissions calculated in MOVES are based on the Vehicle Specific Power (VSP) modal concept. VSP is basically the power required for the engine to overcome the aerodynamic drag, acceleration, rolling resistance, and hill climbing to move the vehicle. MOVES is considered a modal model that calculates emissions for different operation modes such as acceleration, idling, cruise, etc. Specific driving cycles have been specifically developed for each operation mode in the model. It is also recommended that authorities develop their local driving cycles to enhance the emissions estimation.

One of the advantages of MOVES is that the emissions data is collected in real-world driving using Portable Emissions Measurement Systems (PEMS)[9] (Younglove et al., 2005). It is also a relatively easy to use; however, due to its precision and its comprehensiveness, it is extremely sensitive to its input datasets. To understand the impact of the input datasets, a comprehensive sensitivity analysis is conducted in Chapter 5. Since the details and the structure of MOVES are extensive and beyond this study, for

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[9] For introduction on PEMS and laboratory emissions testing you can refer to section 2.2

more details on the algorithm and estimation process you can consult the MOVES guide (USEPA, 2014). Also for a comparison between MOVES and the previous model MOBILE you can refer to Vallamsundar and Lin (2011).

2.4.2 CMEM

Comprehensive Modal Emissions Model (CMEM) is the result of a four-year research project to develop a modal emissions model by the College of Engineering-Center for Environmental Research and Technology (CECERT) at the University of California-Riverside, University of Michigan, and the Lawrence Berkeley National Laboratory. Just like MOVES the model is based on the vehicle's operating modes and the engine power (An, Barth, Norbeck, & Ross, 1997).

CMEM is also designed to interact with a variety of transportation models in various levels of aggregation in terms of time and vehicle type. The temporal aggregation is in three levels: second-by-second, several seconds, and driving cycle. Also, the vehicles can be modeled in three levels: specific vehicle, vehicle/technology, and general vehicle mix. There are two input datasets required to run the model: the control activity input that defines the control parameters of the model, and the vehicle activity input (Barth et al., 2000).

2.4.3 EMFAC

Emissions FACtors (EMFAC) is a conventional emissions model that combines the local vehicles activity data with the emissions factors. Its basic application is to produce emissions factors for on-road motor vehicles at a county, air basin, region, or state level (G. Wang, Bai, & Ogden, 2009). The model is primarily used in California for conformity assessment. The latest version of the model is EMFAC2014 that is pending for the USEPA approval. For more detail on the model you can refer to its users' guide (California Environmental Protection Agency, 2014).

2.4.4 PHEM

Passenger car and Heavy-duty Emissions Model (PHEM) is an instantaneous emissions model based on the modal power demand approach that is used in Europe. PHEM is primarily developed to calculate the Heavy Duty Vehicle's (HDV) emissions factors for HBEFA (Handbook Emission Factors for Road Transport). PHEM calculates the engine power per second having vehicle speed, road gradient, the driving resistance and the losses of the transmission system. For more details on the model and its functions you can refer to Hausberger, Rexeis, Zallinger, and Luz (2009).

2.4.5 TEE

The Traffic Emissions and Energy (TEE) is a model developed by the Italian national agency for new technologies, energy and sustainable economic development (ENEA) since 1992 (Negrenti, 1999). The model was initially developed to answer some of the problems of the average speed models. Fundamentally, TEE is an average speed model but with some corrections to the speed. For the speed correction, referred to as the Congestion Correction Factors (CCF), TEE takes into account the link length, traffic density, link average speed and percent of green time at the intersection. Using the CCF, the model then reconstructs the speed profile. The reconstructed profiles are divided in two groups: free flow cycles (or non-intersection) and intersection cycles. The emissions for these cycles can then be calculated either with the instantaneous speed or the average speed.

2.4.6 VERSIT+

VERSIT+ is an emissions model developed by the Netherlands Organisation for Applied Scientific Research (TNO) in 1987. The model is based on the testing using the dynamometer with 153 actual driving cycles. The model is able to calculate emissions at different geographical scales. At the lowest scale, it calculates emissions on a specific road for each second; and at the highest level of aggregation, it can estimate emissions at a national level. Figure 2.14 demonstrates the main framework of the model. VERSIT+ is considered as a cycle variable model.

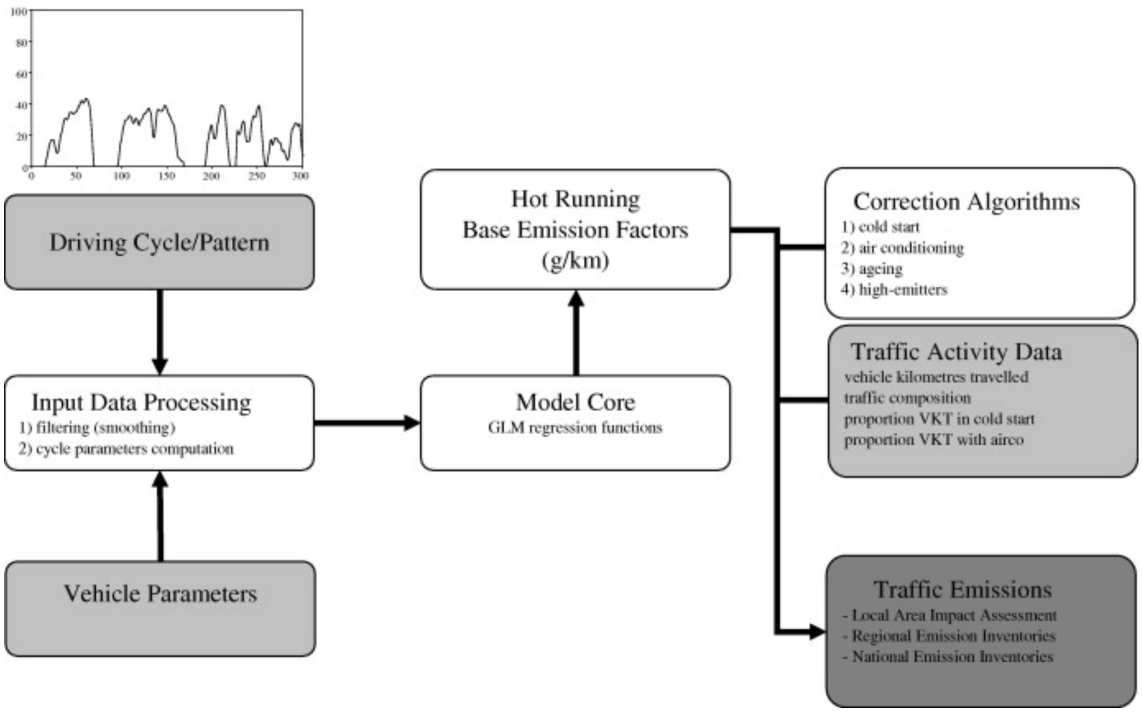

Figure 2.14: VERSIT+ model framework for Light Duty Vehicles (LDV) (Smit, Smokers, & Rabé, 2007)

2.4.7 COPERT

COmputer Programme to calculate Emissions from Road Transport (COPERT) is an emissions calculation model developed in Europe. It is used in several countries in Europe for their official reporting of the national inventories. COPERT is an average speed emissions factor model that calculates emissions in three main blocks: hot emissions (or the emissions produced during thermally stabilized engine operation), excess emissions from cold start, and evaporative emissions (Franco, Fontaras, & Dilara, 2012). COPERT calculates regulated and unregulated pollutants as well as fuel consumption (Gkatzoflias, Ntziachristos, & Samaras, 2007).

2.4.8 HBEFA

HandBook Emissions FActors for road transport (HBEFA) is basically a Microsoft Access database of emissions factors for different vehicle types, road types, and traffic situations. The situations include the speed limit, road gradient and the level of service. The emissions factors within the database are calculated separately using a different emissions model, PHEM (section 2.4.4). HBEFA, like COPERT, calculates emissions for three states: hot engine, cold start, and evaporation (Hausberger et al., 2009).

2.4.9 IVE

The researchers at the International Sustainable Systems Research Center and the University of California at Riverside developed the International Vehicle Emissions (IVE) model to tackle the emissions estimation issue in developing countries. It is a java-based stand-alone computer modal model that is versatile and easy to use. The model requires three types of data (Davis, Lents, Osses, Nikkila, & Barth, 2005):

1- The engine technology and add-on control distribution in the vehicle fleet (as well as maintenance);

2- Driving behaviour of the different types of on-road vehicles traveling on local roads;

3- Vehicle emissions factors specific to the local vehicles

It can estimate emissions from micro to macro scale and is based on the aggregated emissions factor. For the complete structure of the model you can refer to the IVE user manual (IVE model, 2008).

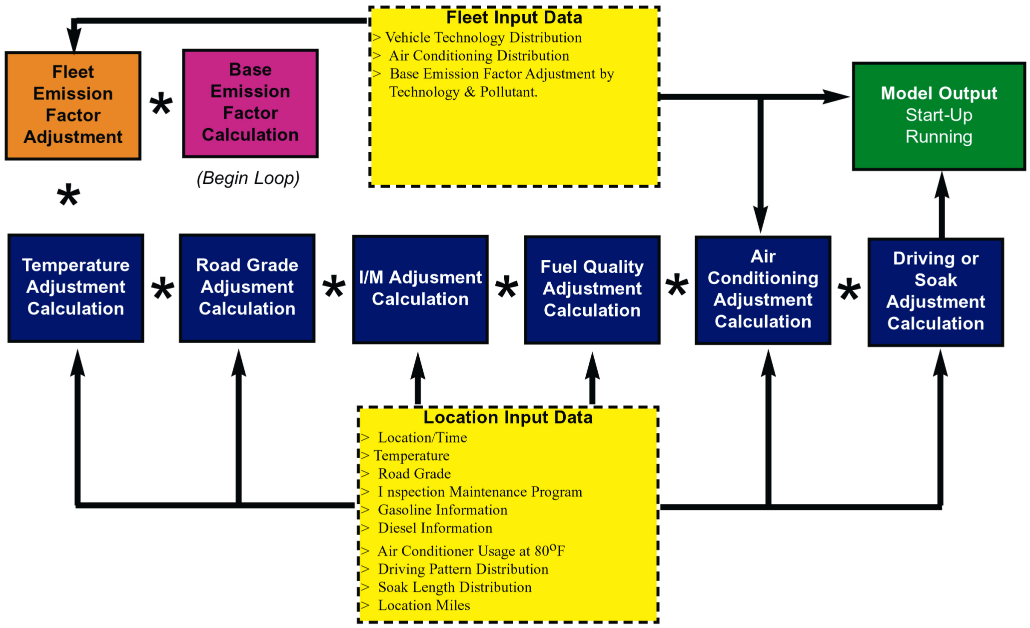

Figure 2.15: Core structure of the IVE model (IVE model, 2008)

2.4.10 Summary

Table 2.5 provides a brief summary of the main emissions estimation models. The modal method is one of the most popular methods that offers accurate results and provides the possibility of instantaneous estimations. MOVES is the main model used in North America currently. Regional characteristics and regulations play an important role in emissions estimation, since the models are based on the local data collection. However, it is important to be aware of the other emissions models to learn from their success and failure to improve the local emissions model. As mentioned before, the geographical focus of this study is Quebec and specifically Montreal; therefore, the further analysis and assessment for improvement is based on MOVES (as used by the Ministry of Transportation Quebec - MTQ).

Table 2.5: The summary of the emissions estimation packages

The model	Model type
MOVES	Modal
CMEM	Modal
EMFAC	Aggregated emissions factor
PHEM	Modal
TEE	Average speed
VERSIT+	Cycle variable
COPERT	Average speed
HBEFA	Traffic situation
IVE	Modal

2.5 Driving cycles

However, before any implementation of policies or mitigation strategies, it is necessary to precisely estimate emissions from vehicles or at least to develop a sufficiently precise and versatile methodology to assess the various types of policies and strategies. The method used in larger scale estimations relies on drive schedules. Drive schedules or driving cycles are speed variations across times that represent typical driving behaviours. Literature has confirmed that driving behaviours and therefore driving cycles are different in different regions (André, Joumard, Vidon, Tassel, & Perret, 2006).

Driving cycles mainly serve two purposes; first the regulatory purpose to calculate the emissions from the manufactured vehicles and enforcing guidelines for vehicle manufacturers to obtain a certain level of emissions; these driving cycles are usually referred to standard cycles. The second use of the driving cycles is for emissions estimation. As they represent driving behaviours in a specific region, under particular traffic conditions, they are the fundamental part of the emissions estimation process. In addition to emissions estimation, the driving cycles can also be used to calculate the powertrain for plug-in hybrid or electric vehicles (Ashtari, Bibeau, & Shahidinejad, 2014). Therefore, the reliability and representativeness of the driving cycles are very critical.

In a comparison between standard driving cycles and real-world driving cycle, authors observe that the standardized cycles can underestimate emissions for the hot running engine phase by almost 50% for petrol engine cars. Whereas, this error is about 10% for the standard cycles (Joumard, André, Vidon, Tassel, & Pruvost, 2000). Different factors can influence driving cycles. On one hand, the factors that actually affect driving behaviours are local regulation, road structure, climate and geography. On the other hand, the methodological approach for constructing a driving cycle does not affect the driving behaviour in reality but affects the representation of the driving behaviour, such as, data collection and cycle construction procedure.

Various methods have been proposed for developing driving cycles but they share a similar structure (Figure 2.16). The principal framework is introduced in Xiao, Dui-Jia, and Jun-Min (2012); it includes:

1. data collection
2. generation of microtrips
3. selection of assessment measures
4. development of driving cycles

Decisions regarding each of these steps can have a significant influence on the reliability and the representativeness of the driving cycles.

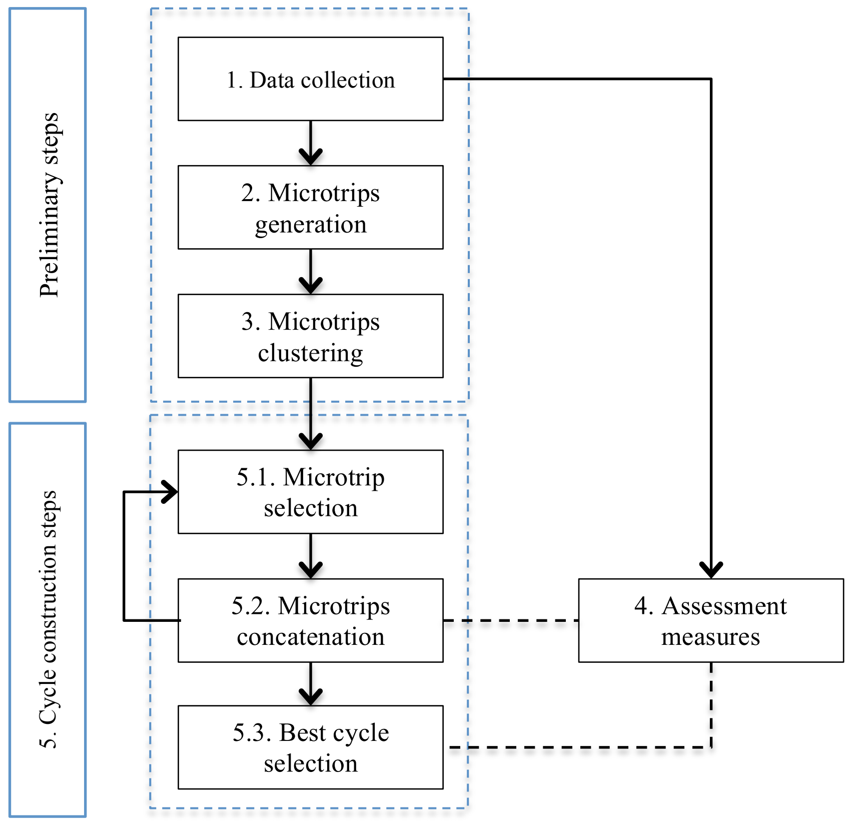

Figure 2.16. General process for developing driving cycles

2.5.1 Step 1: Data collection

The first step for the development of a driving cycle is data collection. Through the history of driving cycle development, various methods have been used largely depending on the technologies available at the time. Based on the equipment and resources available, the procedures and methods can be divided in two main categories: chase car technique and on-board instrumentation. Also, in some studies, both methods are used in parallel.

2.5.1.1 Chase car technique

The car chase technique is one of the first methods used to gather the required data to generate a speed profile. The idea is basically to ask a specific vehicle (chase car), equipped with measuring instruments, to follow a random vehicle (target vehicle) in order to record the activity patterns of the target vehicle or to gather data on patterns similar to the target vehicle. One of the main chase car protocols used in the literature is introduced by Austin, DeGenova, Caelson, Joy, and Gianolini (1993) which explains the procedure to identify a target vehicle and to collect the speed data.

Within the chase car technique two methods can be identified: collecting data from the target vehicle using the laser technology, and collecting the data from the chase car also known as non-lock data. Morey, Limanond, and Niemeier (2001) in a comparison between these two methods, explain that although results of the two methods are comparable at an aggregated level, they show important differences at the disaggregate level and hence the choice of a method over the other can affect the representativeness of the driving cycles. They justify that the quality of non-lock data largely depends on the ability of the chase car driver to imitate the target vehicle's driving.

Some of the studies that have used chase car technique are: P. G. Boulter, Latham, and Ainge (1999), Schifter, Díaz, Rodríguez, and López-Salinas (2005), Kamble, Mathew, and Sharma (2009), and Hung, Tong, Lee, Ha, and Pao (2007). The main advantage of this method is the randomness of the target vehicle and the ability to collect data for large number of vehicles. However, such approach can only record a specific section of the driver's trip and can miss some details of the entire trip. Therefore, it is preferred to use the on-board instrumentations.

2.5.1.2 On-board instrumentation technique

With the new technologies, new possibilities have become available to gather vehicle speed data. This approach limits the human intervention required. The new data collection devices can be very small and can be left on the vehicle for a longer time, allowing to record activities over a longer period and without necessary inputs from the drivers. This technique can be segmented in two categories: instructed method (i.e. asking the user to drive on predefined routes) and uninstructed method (i.e. asking the user to drive on its regular everyday routes).

Selection of the route is the principal component of the predefined route method. The selection of the route can be either systematic based on the traffic data or un-systematic based on the simple judgment of the researchers. The non-systematic method is used in different studies such as: Tong, Hung, and Cheung (1999), Esteves-Booth, Muneer, Kirby, Kubie, and Hunter (2001), Shi, Zheng, Wang, and Li (2011), Montazeri-Gh and Naghizadeh (2007), and Fotouhi and Montazeri-Gh (2013). However, it is discussed that the non-systematic method can be very biased due to the fact that it is based on the researchers' personal opinion.

The main purpose of the systematic method is to find representative routes that can cover all typical driving patterns in the city objectively. Two examples of the systematic route choice are presented in Tamsanya, Chungpaibulpattana, and Atthajariyakul (2006) in which the selection is based on the speed and flow distribution on the network, and Hung et al. (2007) that used the Annual Average Daily Traffic (AADT) data to identify relevant routes. Also, in another study Li, Chaosheng, Minghui, and Shuming (2008) took the road grade into consideration besides the speed and volume.

The other on-board instrumentation technique that is widely used is the uninstructed method by distributing the on-board devices to regular drivers and recording their everyday normal usage. This method is very well favoured due to its simplicity, relative low cost, and reduced professional intervention. One of the firsts and most comprehensive data collections were done in Europe as presented by André, Joumard, John Hickman, and Hassel (1994) followed by André (2004a). The data covers 77 vehicles, 2000 days, 10,300 trips, 88,000 km, 2200 h of driving in 6 countries. The amount of data is particularly important as it allows developing a representative cycle. Another example of using this technique is presented in Ashtari et al. (2014); data collection is conducted in Winnipeg, Canada, using 76 participants from May 2008 to June 2009. In this technique, the recruitment procedure plays an important role and should be designed in order to avoid exclusion of any specific driving pattern. The samples usually cover different vehicle types and annual mileages (André et al., 2006) as well as a wide range of driver profiles such as income bracket, education level, gender and area of the city (Ashtari et al., 2014).

The last technique, the on-board instrumentation with the normal everyday driving, is believed to be the most comprehensive and efficient technique since it can cover a wide range of situations without any input from the researcher.

When data have been gathered and structured into a database, the next step is the generation of microtrips.

2.5.2 Step 2: Generation of microtrips

It is almost impossible to define the average driving pattern by considering the entire trips. Therefore, the trips are usually divided into smaller trips representing significant driving patterns, which are called microtrips. The most basic definition of a microtrip is a sequence of speed profile between two successive stops (Xiao et al., 2012). This definition is used in most of the studies; hence, in studies where the microtrips' generation method is not discussed, we assume that the sequence between two stops is used.

However, it is argued that the sequence between two successive stops may not reflect the driving behaviour in local roads since urban driving usually consists of very short sequences, which makes the analysis hard and biased (André, 2004a). Urban driving in congested conditions usually translates into constant and frequent stops; therefore the microtrips are very short and those very short segments are usually purged during the data preparation. The microtrips under 10 seconds are usually eliminated. Consequently, this method undermines the congested urban driving patterns, which are not negligible for vehicle emissions estimation. Therefore, André (2004a) has proposed using homogenous time intervals to segment trips into microtrips.

The other simple method that is used by Esteves-Booth et al. (2001) is based on speed range. Based on this method the trips are divided by classes of speed and acceleration. Every time speed passes a certain point, a new microtrip is started until it reaches the maximum speed of that class.

The other definition of microtrips introduced by Lin and Niemeier (2003) is a clustering approach based on acceleration data. Other researchers have adopted this method as well (Ashtari et al., 2014; Shi et al., 2011). Lin and Niemeier (2003) used maximum likelihood estimation algorithm for clustering; whereas in Ashtari et al. (2014) they used k-mean clustering method. Based on this method the speed data is then clustered into different categories called "event", where an event is related to an acceleration mode such as quasi-cruise event, acceleration event, etc.

2.5.3 Step 3: Microtrips' classification

After dividing the trips into the microtrips the next step is classifying the microtrips into different categories representing different driving patterns. The average speed, acceleration and the proportion of idle time are the factors that are commonly used to classify the microtrips. The classification methods can range from a basic procedure such as simple judgment of the researcher to more complex clustering algorithms.

In one application of the simple method, Montazeri-Gh and Naghizadeh (2007) classified the microtrips based on the traffic conditions identified by the correlation between the average speed and idle time divided by total time of the microtrip. In a another study, Fotouhi and Montazeri-Gh (2013) used the same factor (average speed vs. idle/total time) but this time by integrating the k-mean algorithm for clustering. The k-mean clustering method is also used in Ashtari et al. (2014). In another study André (2004a) used the chi square distance on the Speed Acceleration time Frequency Distribution (SAFD) to define different driving pattern. Also Jie and Niemeier (2003) introduced event bins, which is basically different acceleration profiles and then used the maximum likelihood estimation to classify the modal events into distinct bins.

2.5.4 Step 4: Selection of assessment measures

Before building a driving cycle, certain criteria should be identified to assess its performance. Assessment measures are the overall factors identified that represents the target characteristics of the driving cycle. As emphasize Xiao et al. (2012), identifying the target values or the assessment measures is a critical step. The target values can represent all driving data or just certain trends in the database. In different studies, various assessment measures have been used; however, they are mostly related to speed and acceleration. Regarding speed, the target values can be average speed, average in use speed, standard deviation of speed, maximum and minimum speed, etc. Also regarding the acceleration, some of the target values are average acceleration or deceleration, maximum and minimum acceleration, standard deviation, 95th percentile, root mean square, time proportion (acceleration, deceleration, cruising, creeping), etc. These assessment measures can be used while or after producing the driving cycle depending on the microtrip selection method. The last step in developing a driving cycle is concatenating the microtrips.

2.5.5 Step 5: Development of driving cycles

There are two main methods for concatenating the microtrips: stochastic method and Marcov-chain process. In the stochastic method, the microtrips are randomly selected from each cluster. The only criterion is to keep the proportion of microtrips from each cluster same as the target value. The target value can be the proportion of the microtrip cluster for the entire database or for a specific driving cycle.

In the other method (André, 2004a; Ashtari et al., 2014; Jie & Niemeier, 2003) the probability of events happening in succession is defined by a Marcov-chain process based on the transition matrix. In this method, the first microtrip is chosen randomly and then based on the probability of the next cluster happening in the database, the next microtrip is chosen from that cluster.

As we can see, there are different methods for each step of the driving cycle development. In some cases the researchers have reached agreement regarding which method is more efficient and comprehensive. For example, for data collection, the on-board uninstructed method is preferable. Similarly, in the final step, using a transition matrix has been identified as the more appropriate approach in more recent applications. Also, the assessment measures for choosing the best driving cycle are very similar in most studies and are initially based on an early study by Kuhler and Karstens (1978) with minor differences. Meanwhile, two steps have received less attention in the literature namely methods for defining the microtrips and clustering methods. In this study, we focus on the definition of microtrips. To fulfill our analysis different datasets is used; next chapter introduces the datasets as well as the data collection procedure.

2.6 Sensitivity analysis

As mentioned briefly in the introduction, two of the objectives are based on the sensitivity analysis. The first objective was to detangle the available emission model and demonstrate the impact of each variable. Also, the second objective was to discuss the sensitivity of the MOVES towards its input databases. Both analyses are done using sensitivity analysis methods.

Sensitivity analysis (SA) is a statistical method that enables an understanding of how the output of a model is influenced by the input datasets (Saltelli, Chan, & Scott, 2000). SA has various applications in the process of modeling including diagnostic studies and forecasting. It can assist the modellers to prioritize the measurement or calibration of the most influential factors for enhancing the simulations. Depending on the objectives and nature of the model there are different methods available. Saltelli et al. (2000) have classified the methods in 3 main groups: screening, local SA, and Global SA.

The screening method is based on a sampling method and is usually used to identify the inputs or variables that contribute to the output rather than to quantify the impact. Besides, both local and global sensitivity analyses aim to calculate the impact of variables on the output. Each of these methods has advantages and weaknesses. For instance, screening is computationally economical and can offer the rank of the input factors in order of importance; however, it cannot quantify the magnitude of the importance. On the other hand, the local SA enables quantifying the significance but is not very helpful for comparing the impact of different factors at the same time. In this study, the global SA is used which enables us to evaluate the effect of various variables in their whole range of variation.

CHAPTER 3 INFORMATION SYSTEM

The Montreal metropolitan area is, with 3.9 million inhabitants (in 2011), the most populated city in Canada after Toronto. Just in the island of Montreal, amongst 879,000 vehicles which are driven on the network, 82% are passenger cars (Ville de Montréal, 2011); they are responsible for 66% of the total CO_2 emissions (Figure 3.1). Gasoline is the main fuel consumed, the share of other fuels being very small (Natural Resource Canada, 2008). The network of this study area is composed of about 40,311 links and amount to some 26,200 km. These statistics just confirm the significant role of private vehicles in transportation and therefore the CO_2 emissions. The emissions analysis requires different types of information; the databases used in this study are discussed in this section.

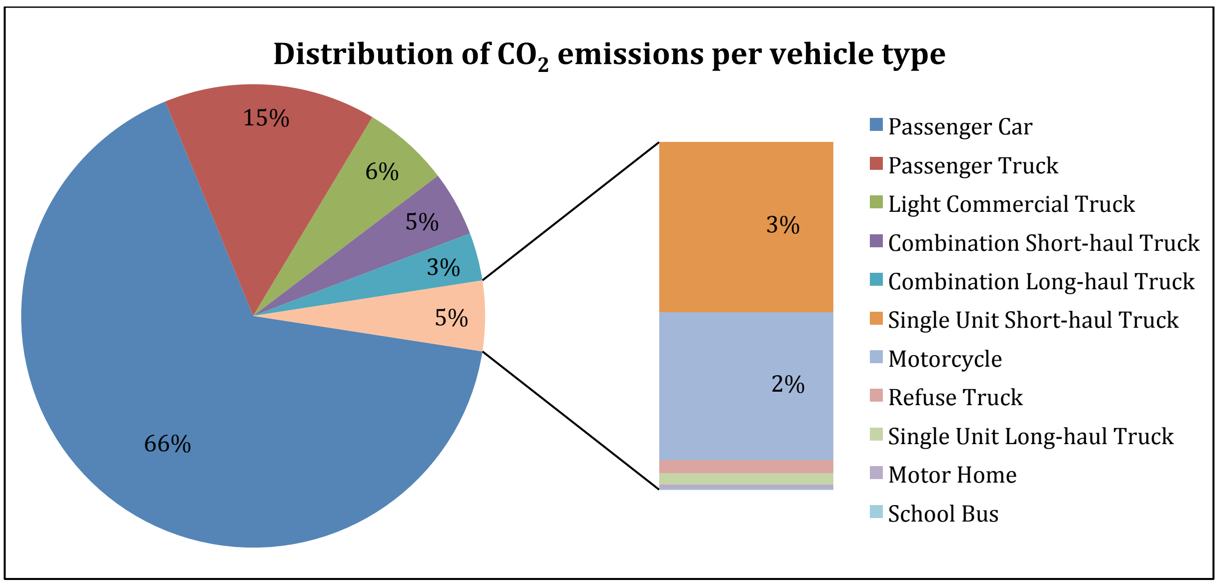

Figure 3.1: Distribution of total CO_2 emissions per vehicle type (calculated by Quebec Ministry of Transportation using MOVES)

3.1 Data collection

One of the main data required in vehicle emissions estimation is the vehicle activity data. In an effort to record the driving behaviour in Montreal, an activity database was collected. The data used for this study is based on a three-day data collection using a datalogging device equipped with GPS connected to the OBDII port of a vehicle. This device records the speed and geographical position of the vehicle per second. Other data such as instant fuel consumption, engine coolant temperature, and instant fuel economy were also recorded, but not used in this study, since the fuel consumption data demonstrated high anomalies. To fully understand the sources of these anomalies and to develop the required processes for making these data usable for research, further investigation is required. However, since the fuel consumption data were not required for the development of the driving cycles, these steps will be conducted further in time. The data logger is DashDynoSPD, bought from Auterra Company; it is shown in Figure 3.2.

DashDynoSPD OBDII

Figure 3.2: Data collection equipment and OBDII demonstration

The data recording frequency was not constant and changed based on the amount of information and the vehicle computer’s speed; but it was always at least once per second. The collected data was then transferred to CSV files using the Dyno-Scan application, software provided by the company. Eight students (all at Polytechnique Montreal) volunteered to drive the vehicle; they were asked to drive as they typically do. The vehicle was a conventional gasoline Toyota Yaris rented from Communauto, a carsharing company operating in Quebec.

In section 2.5.1, we discussed the available methods for data collection. As mentioned, the data collection can be instructed (based on a specific route) or uninstructed (everyday normal driving routes and habits). Both methods have their advantages and disadvantages and can be useful depending on the purpose. Since limited resources were available, the instructed method was selected.

The data collection was conducted at the end of January 2014 during a 3 days period from 7 am to 10 pm, covering a variety of traffic conditions: peak as well as non-peak hours on residential streets and highways. The selected route covers various types of urban roads: residential, collector, boulevard, and highway. The selected route is about 20 km long and takes on average about 43 minutes to complete (one lap).

The fastest lap was 38 minutes long with 31 km/h average speed, collected in early morning. Also, the slowest lap took 63 minutes to complete with the average speed of 19 km/h during the evening rush hour. In total 45 laps were recorded. During the observation days, the temperature varied between – 14 °C and +1 °C (-19 °C and -5 °C considering wind factor) with no considerable precipitations. Figure 3.3 demonstrates the selected route on the map.

Figure 3.3: The selected route for data collection

After cleaning the database, some 35 hours of useful data were available for further analysis. Some of the data was deleted due to GPS errors or drivers' mistakes in taking a route. Also, the data related to entering and exiting gas stations was removed. Table 3.1 summarises the main global statistics of the dataset. Also, as Figure 3.4 demonstrates, the majority of the driving behaviour reflects the urban driving behaviour with lower speeds and a large number of stop and go patterns.

Table 3.1: The global descriptive statistics of the dataset

Statistics	**Value**
Total time	35:19:49
Total distance traveled	898.66 km
Average speed	25.42 km/h
Maximum speed	103.85 km/h
Standard deviation of speed	19.62 km/h
Maximum acceleration	1.97 m/s^2
Standard deviation of acceleration	0.55 m/s^2
Number of laps	45
Number of drivers	8

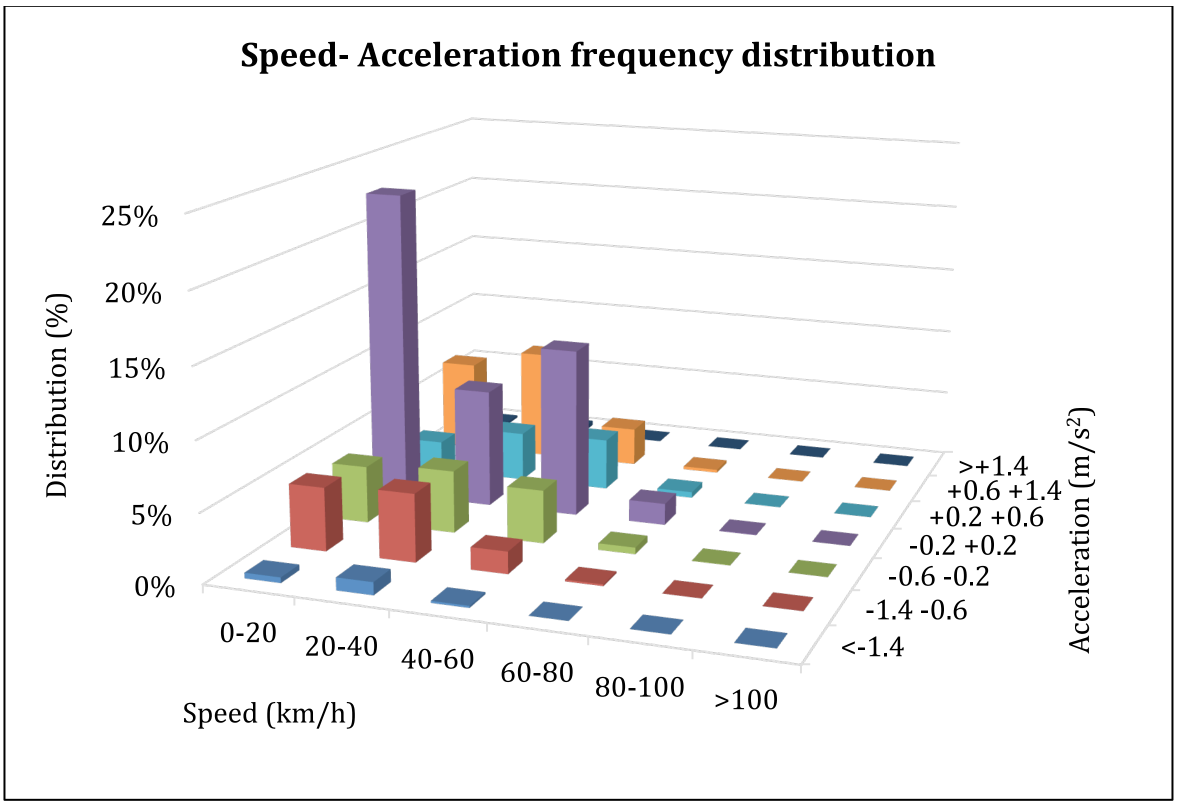

Figure 3.4: Speed-acceleration frequency distribution of the dataset

In emissions analysis or in general the transportation planning studies, the speed or driving behaviour is evaluated at link level. A link in this study is the road section between two intersections. Within the selected route, about 80% of the links are less than 300 m (Figure 3.5). The global average link speed is 25 km/h with the most frequent values being between 15 and 45 km/h. Since the chosen route covers a short distance on the highway, most of the driving reflects low speed urban driving behaviour (Figure 3.6). This dataset is used in this study to evaluate the available fuel consumption models (Chapter 4) as well as to develop a local driving cycle (Chapter 6).

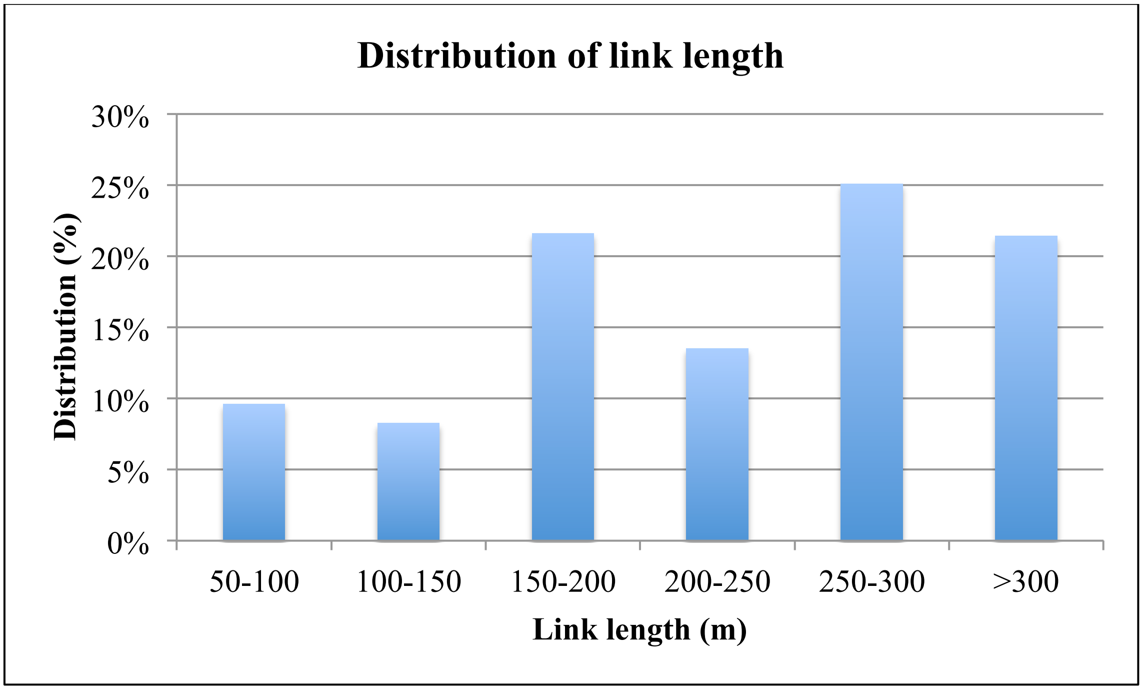

Figure 3.5: The road link length distribution

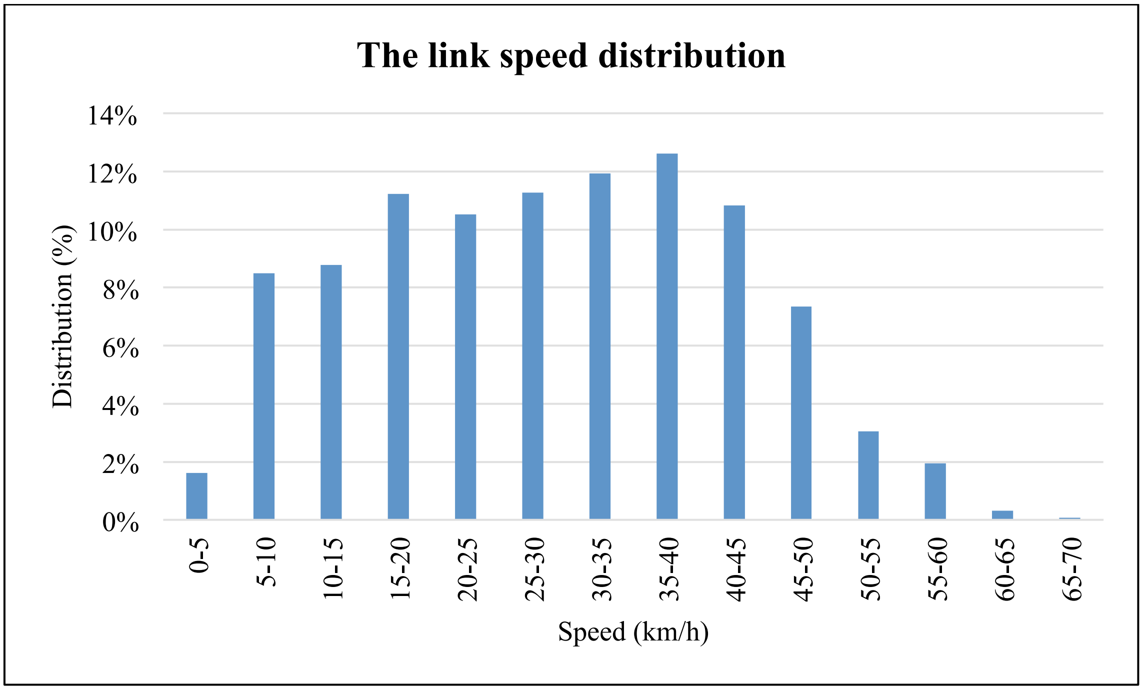

Figure 3.6: The link speed distribution

There were a few challenges in the data collection process. First, due to the drop in temperature the data logger did not record correctly the first few hours of the trip each day until the vehicle was warmed up; however, we were able to retrieve the location data from the additional GPS and speed and distance were calculated with the location data. Also, in the middle of the second day, because of a technical problem, we had to change the first car but the second car was the same make and model. The age, the kilometers traveled, and the year of the vehicles were not the same. However, both vehicles were similar enough not to have any impact on the driving behaviours of the drivers.

Regarding the drivers, because of the limited data, it was difficult to distinguish any personal driving habit. To be able to identify specific driving behaviour we need to collect data of different drivers under same condition such as time of the day, traffic condition, etc. For future data collection, with more resources, it would be interesting to record data on a larger number of drivers with different profiles as well as different types of vehicles. Both, the drivers' profile (age, sex, occupation, etc.) and the vehicle type can have an important influence of the driving patterns.

It is also important to note that the acceleration was calculated from speed. However, instead of considering the speed as two consecutive seconds, an average of 5 seconds (2 seconds before and 2 seconds after) was considered since the acceleration usually does not change instantaneously in a vehicle and the instantaneous calculation can result in unreasonable large acceleration or deceleration values. This dataset was used in both Chapter 4 and Chapter 6.

3.2 Weather data

The other main dataset used in this study is the historical weather data retrieved from Government of Canada website[10] (Figure 3.7). The data can be selected with different aggregation level: hourly, daily, and monthly. The hourly data was used in this study. The database consists of data on temperature, humidity, wind speed, wind direction, visibility, atmospheric pressure, wind chill, and the weather condition (such as being cloud, fog, tornado, snow, freezing rain, etc.).

The dataset is used to demonstrate the variability of Montreal's weather conditions and to explain how the local weather can influence the vehicle emissions. For example, the cold start increases the vehicle emissions significantly; but the magnitude of importance might not be the same for different regions. For example, for regions that do not experience the extreme cold conditions (e.g. India), the contribution of cold start in total emissions would not be significant, comparing to the contribution of air conditioning.

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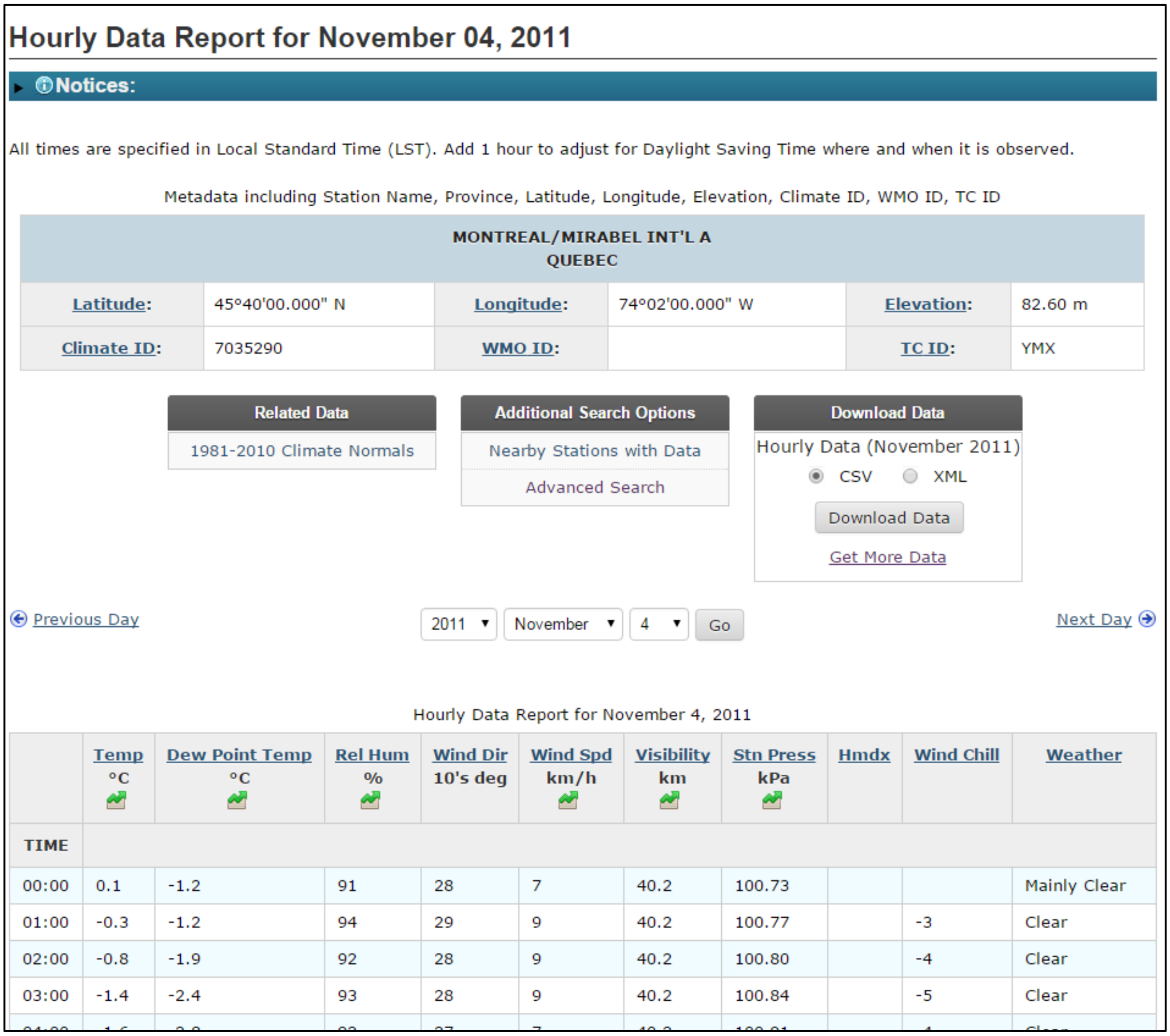
[10] http://climate.weather.gc.ca/



Hourly Data Report for November 04, 2011

▸ ⓘNotices:

All times are specified in Local Standard Time (LST). Add 1 hour to adjust for Daylight Saving Time where and when it is observed.

Metadata including Station Name, Province, Latitude, Longitude, Elevation, Climate ID, WMO ID, TC ID

MONTREAL/MIRABEL INT'L A QUEBEC					
Latitude:	45°40'00.000" N	Longitude:	74°02'00.000" W	Elevation:	82.60 m
Climate ID:	7035290	WMO ID:		TC ID:	YMX

Related Data
1981-2010 Climate Normals

Additional Search Options
Nearby Stations with Data
Advanced Search

Download Data
Hourly Data (November 2011)
CSV XML
Download Data
Get More Data

Previous Day 2011 November 4 Go Next Day

Hourly Data Report for November 4, 2011

	Temp °C	Dew Point Temp °C	Rel Hum %	Wind Dir 10's deg	Wind Spd km/h	Visibility km	Stn Press kPa	Hmdx	Wind Chill	Weather
TIME										
00:00	0.1	-1.2	91	28	7	40.2	100.73			Mainly Clear
01:00	-0.3	-1.2	94	29	9	40.2	100.77		-3	Clear
02:00	-0.8	-1.9	92	28	9	40.2	100.80		-4	Clear
03:00	-1.4	-2.4	93	28	9	40.2	100.84		-5	Clear

Figure 3.7: An example of the historical data provided by Government of Canada website

As demonstrated in Figure 3.8, Montreal has a varied temperature that can change within a wide range (60°C, +/- 30°C around freezing point). Around 25% of the time (year), the temperature is below freezing point. Also, it is discussed that the comfortable outdoor temperature is between 18°C and 23°C (Honjo, 2009); around 70% of the time the temperature is below the thermal comfort. This database is used in Chapter 4 and Chapter 5.

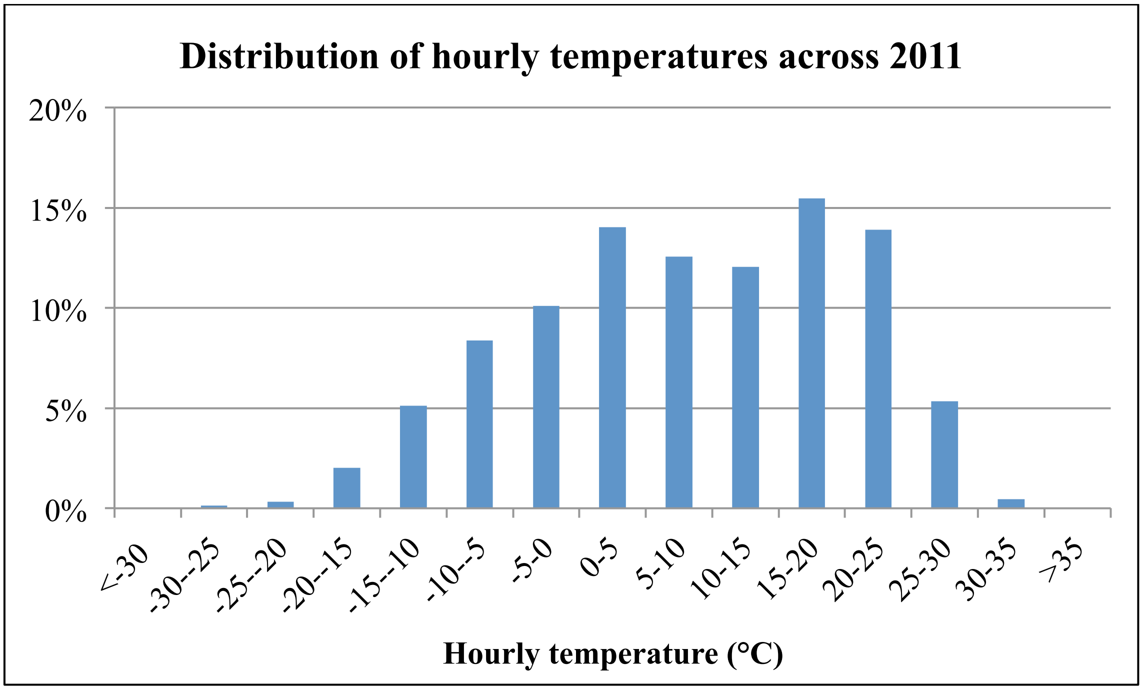


Figure 3.8: Hourly temperature distribution in Montreal throughout 2011

3.3 Fuel consumption and vehicle characteristics data

In this study, fuel consumption and vehicle characteristics data are used to demonstrate the impact of vehicle specification on fuel consumption. For this purpose, different open source datasets and websites are used. For example, for some examples of average idle fuel consumption, the data was retrieved from the Office of Energy and Renewable Energy (OEERE) website (Office of Energy Efficiency and Renewable Energy, 2015). In the information they provided the average engine size, vehicle weight and idle fuel consumption of different vehicle classes was used in this study. Also regarding the aerodynamic coefficient and the vehicle weight, the information was found from multiple resources such as ecomodder website ("Vehicle Coefficient of Drag List," 2015) and the vehicle's company website.

CHAPTER 4 CALCULATING EMISSIONS AND THE IMPACT OF INFLUENCING FACTORS

In the previous section, a comprehensive review of the available emissions models was presented. There are various approaches towards fuel consumption or emissions estimation mainly depending on the purpose of the analysis. Some are microscale, with a focus on vehicle characteristics and activity or pavement design, capturing as many details as possible, while others are simplistic models correlating fuel consumption to just a few variables. Each of these perspectives has its advantages and disadvantages. Microscale models are more accurate and can reflect the change in each variable, but they require an extensive amount of data and the calculation time might become impractically long. On one hand the simplistic models are mainly developed to cover that problem; however, they are unable to reflect changes in detail. For example, using an average speed model, the impact of traffic smoothing cannot be captured if it does not have any influence on the total average speed on the link. It is therefore crucial to understand the magnitude of the contributions of every factor to be conscious of the trade-off between accuracy and simplicity.

Also, this analysis can provide a good understanding of the priorities for reducing the emissions or modeling emissions. For example, if we know that cold temperature has relatively high impact on fuel consumption, first we can focus on the analysis of the temperature on emissions and collect more reliable data and improve the model from that perspective. Also, in regards to policy making, although it is not possible to change the temperature there are strategies such as encouraging indoor parking or implementing a higher tax or fees for outdoor parking that can have an influence on the cold-start excess emissions.

4.1 Methodology

As mentioned briefly before, the main objective of this section is to evaluate and compare the contribution of different factors on CO_2 emissions. To do so, a sensitivity analysis is conducted. There are several sensitivity analysis methods. In this study the global sensitivity analysis was selected, since it can evaluate the effects of different variables through a whole range of variations (Saltelli et al., 2000). The structure of the methodology has two main elements: the models to estimate and the input data.

Several databases are used to develop the scenarios for the sensitivity analysis: real-world speed, weather, and vehicle characteristics. Regarding the vehicle speed, the real-world driving database, collected for this study, is used. The speed is analyzed both at an instantaneous scale and through the average on a link. A link is defined as a section of a network between two intersections. The intersections are not necessarily signalized; also, the vehicles may have or may have not stopped at the intersections. Also the historical weather data was acquired from the Environment Canada website. The details of the data collection and the resulting database as well as the weather variations are presented in section 3.1. The vehicle specifications such as aerodynamic coefficient, weight, and idle fuel consumption are retrieved from various websites such as ecomodder, the companies', and the Office of Energy Efficiency and Renewable Energy (OEERE) websites (Office of Energy Efficiency and Renewable Energy, 2015; "Vehicle Coefficient of Drag List," 2015).

The vehicle that is used for this analysis is a fictive passenger vehicle. In the analysis, the correlations between variables are not accounted for. For example, there is a relation between engine capacity and vehicle weight as well as the vehicle's weight and its size, but in this study, this is not accounted for. Firstly, due to the fact that in the analysis we chose to evaluate one variable at a time. Also the relation between vehicle size and vehicle weight does not follow a specific pattern. For instance, more recent vehicles can be lighter despite their larger size.

To select the appropriate model, several factors were considered: the comprehensiveness, level of detail, and the recentness. Each model had certain challenges regarding these factors. For example the model that was introduced and updated by Akçelik et al. (2014) is the most cited instantaneous power demand model available in the literature (presented in section 2.3.1.5) ; it is however missing some details regarding the vehicle and pavement characteristics due to the simplification. Therefore, it is not possible to evaluate the impact of vehicle type. On the other hand, most of the detailed model focused on either one or just a few variables, such as the rolling resistance model, developed by Karlsson et al. (2011).

To analyse the variables, first the proper equation was chosen. Few factors were taken into consideration to choose between different models. The first factor was the comprehensiveness of the model. Some of the equations in the available studies are either simplified or have been estimated using constants that reflect the condition or the fleet of a particular study context and area. Also, the year of the study was the other factor used to choose the best and up-to-date model for our analysis.

After evaluating different power demand model, the model provided in Leung and Williams (2000) was selected. Equation 4-1 is the expanded form of the Equation 2-2, discussed in page 44. The definition and the unit of each variable are also provided in that section. However, the model has a few shortcomings: it does not reflect the impact of pavement texture and the speed of wind as well as any estimation of the auxiliary power demand. Therefore, some measures are taken into consideration to enable the evaluation of these factors.

$$\begin{aligned} FC = 8.5 \times EC + \beta(&2.36\times10^{-7} v^2 M + (3.72\times10^{-5} v + 3.09\times10^{-8} v^2) M \\ &+ 1.29\times10^{-5} C_\mathrm{d} \mathrm{A}\, (v + v_w)^3 \\ &+ 2.78\times10^{-4} (a + g \sin\theta)\, M\, v) \end{aligned} \qquad \text{Equation 4-1}$$

Where,

FC = Instantaneous fuel consumption (ml/sec)
EC = Engine capacity (L)
β = Engine efficiency factor (ml/sec)
v = Speed (km/h)
M = Vehicle weight (kg)
C_d = Vehicle aerodynamic coefficient
A = Frontal area (m^2)

v_w = Wind speed (km/h)
a = Acceleration (m/s^2)
g = Gravity of earth, 9.8 m/s^2
θ = Road grade (radian)

To implement the impact of wind, based on the Jimenez-Palacios (1999), Equation 2-5 is replaced by the aerodynamic resistance calculation in the initial model. Also, regarding the rolling resistance, at first it was intended to replace the rolling resistance with a more sophisticated model provided in Karlsson et al. (2011). However, the results were incoherent with the results of the rolling resistance in the power demand model. Therefore, to reflect the range of possible variations we will restrict the percentage of change to the total rolling resistance proportionally. That is the impact of each variable (namely, MPD and IRI) is calculated on the rolling resistance and the results in terms of percentage change is applied in the initial results estimated in the power demand model. For example, we change the IRI by 1 and the rolling resistance changes by 10% comparing to the previous value, we apply the 10% variation to the rolling resistance calculated by the initial equation to calculate its influence on the total fuel consumption.

For the sensitivity analysis, global sensitivity analysis method is used. However, the first challenge was to compare variables that are not comparable in terms of characteristics and definitions. For example, how can we compare speed to temperature and how much change in temperature represents a certain change in vehicle weight? To answer this question, we approached the variables in their realistic ranges of variations. For example, among the available vehicles (not considering the prototype vehicles that are not yet commercialized) the lightest vehicle was 800 kg and the heaviest 2800 kg. A possible range was then defined for each variable; also, regarding the factors that are dependent to the specific local conditions (i.e. temperature, and wind speed) the Montreal's data was selected.

In this study, the global sensitivity analysis method is used. To do so, a fictive car is defined in a fictive situation, and then for each variable, a maximum and minimum is defined and the impact of 10% variation of the variable on the fuel consumption is calculated with respect to the minimum value for fuel consumption. Table 4.1, demonstrates the minimum and maximum value identified for each variable.

Table 4.1: The variation range of the variables

Variables	Minimum	Maximum
Vehicle weight (kg)	800	2800
CdA (m^2)	0.28	1.56
Engine capacity (litre)	1	6
Engine efficiency factor (ml/kW) (smaller number corresponds to higher efficiency)	0.1	0.2
Road grade (degree)	0	5
IRI (mm)	1	4
MPD (mm)	0.5	1.5
Speed (km/h)	0	70
Temperature (°C)	-30	+30
Wind speed (km/h)	0	60

4.2 Results and discussion

The analysis is organized in four sections: the vehicle characteristics, the driver's behaviour, the environment, and the road characteristics. In the first step, each variable is evaluated separately, while the rest of the variables are kept at their minimum value. In the second step, groups of variables are modified together to evaluate the impact of the change of more than one variable at a time. To do so, two approaches were taken into consideration. First, a maximum and minimum emission was calculated by using maximum and minimum value for all the variables. The results help to highlight the maximum possible impact of all variables. However, in real situation, the extremes do not occur very often. Therefore in a second step different realistic situations are introduced to discuss the impact of multiple variables in real-world contexts.

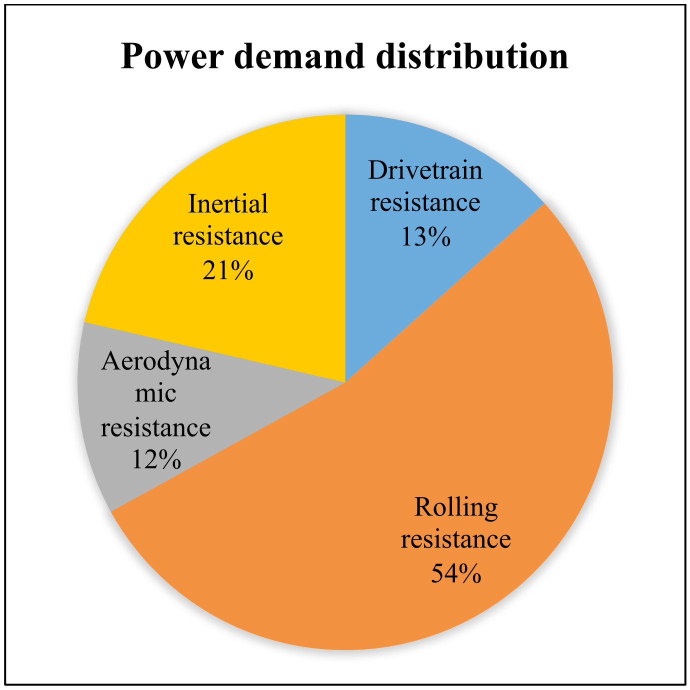


Figure 4.1: The power demand distribution for the entire collected dataset

4.2.1 Vehicle characteristics

Different characteristics of the vehicle, including weight, aerodynamics, engine capacity, and engine efficiency are evaluated. Regarding the vehicle's weight, the passenger vehicle can vary between 800 kg (e.g. two-seater Smart car) to about 2800 kg (e.g. Lincoln, Navigator). The analysis revealed that every 10% increase in weight (200 kg) can increase fuel consumption by 11%. This 11% variation is only the result of the vehicle's weight increase, however, it should be noted that heavier vehicles usually have more powerful engines and therefore more engine capacity. For example the Lincoln Navigator has a 5.4 L engine ("Lincoln Navigator,"). Also, regarding the engine capacity, each 10% increase in capacity increases fuel consumption by about 25%.

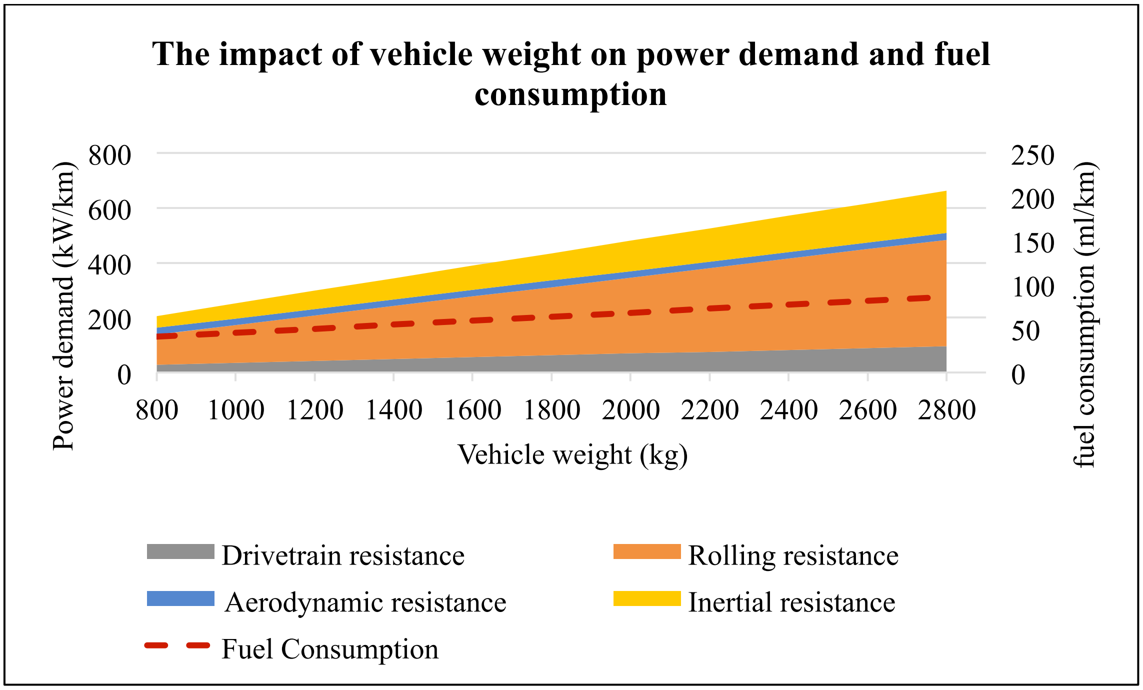


Figure 4.2: The impact of vehicle weight on power demand and fuel consumption

In addition to weight and engine capacity (engine displacement), the aerodynamics of a vehicle are among the main characteristics. One of the most aerodynamic vehicles is the Volkswagen XL1 with Cd of 0.19 and A of 1.47 m2 (CdA= 0.28) and one of the least aerodynamic in the light cars genre is the Mercedes-Benz G class with an aerodynamic coefficient of 0.53 and frontal area of 2.94 (CdA = 1.56) ("Vehicle Coefficient of Drag List," 2015). Also Table 4.2 demonstrates the aerodynamic measures of the most popular cars in Canada. In addition to the vehicle's aerodynamic measures (frontal area and the aerodynamic coefficient), the vehicle's speed and the wind speed can affect aerodynamic resistance. Based on our collected data, on average, every 10% deterioration in aerodynamics can increase the resistance by about 45% and increase the total fuel consumption by about 3% (Figure 4.3).

Table 4.2: Best selling cars in 2014 in Canada

Make and model	Cd (aerodynamic coefficient)	A (frontal area)	CdA
Honda Civic	0.29	1.96	0.57
Hyundai Elantra	0.32	2.13	0.68
Toyota Corolla	0.29	2.09	0.61
Mazda 3	0.26	2.26	0.59
Chevrolet Cruze	0.31	2.22	0.69

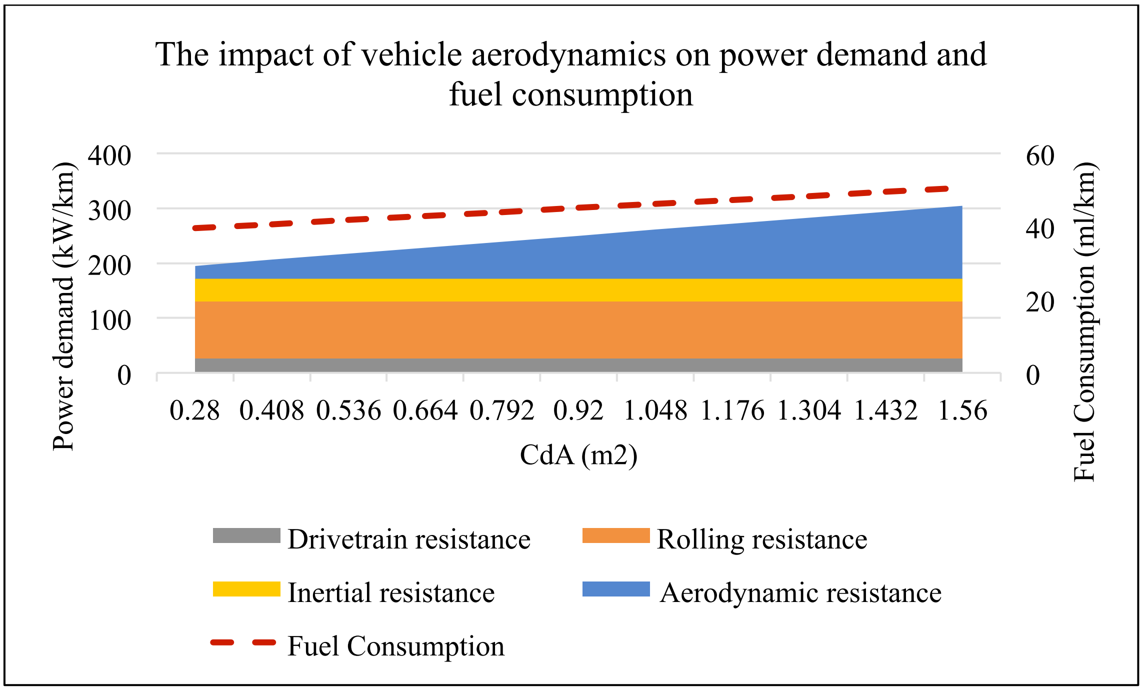


Figure 4.3: The impact of vehicle aerodynamics on power demand and fuel consumption

In addition to the previous factors, the engine efficiency also has an important influence on emissions. Using the power demand equation, the engine efficiency is translated into the ml of fuel required for each kW. In the initial study of the Leung and Williams (2000) the coefficient β is 0.2, whereas in more recent study, using the same type of model, it is set as 0.1 (Akçelik et al., 2014). The value of this coefficient is usually calculated by regression analysis while already having obtained the rest of the variables. As a result, with a 10% change in the efficiency the fuel consumption changes by 6%

4.2.2 Speed profile

The impact of the speed on emissions being produced is determined in terms of average speed on the link, and the link is defined as the section of a network between two junctions either with or without signal. This definition is used for the average speed since the speed data is usually available on the link level. As we can see in Figure 4.4, the average can be defined across time or distance. In this analysis the distance-based approach is selected since the activity data is often calculated as VKT.

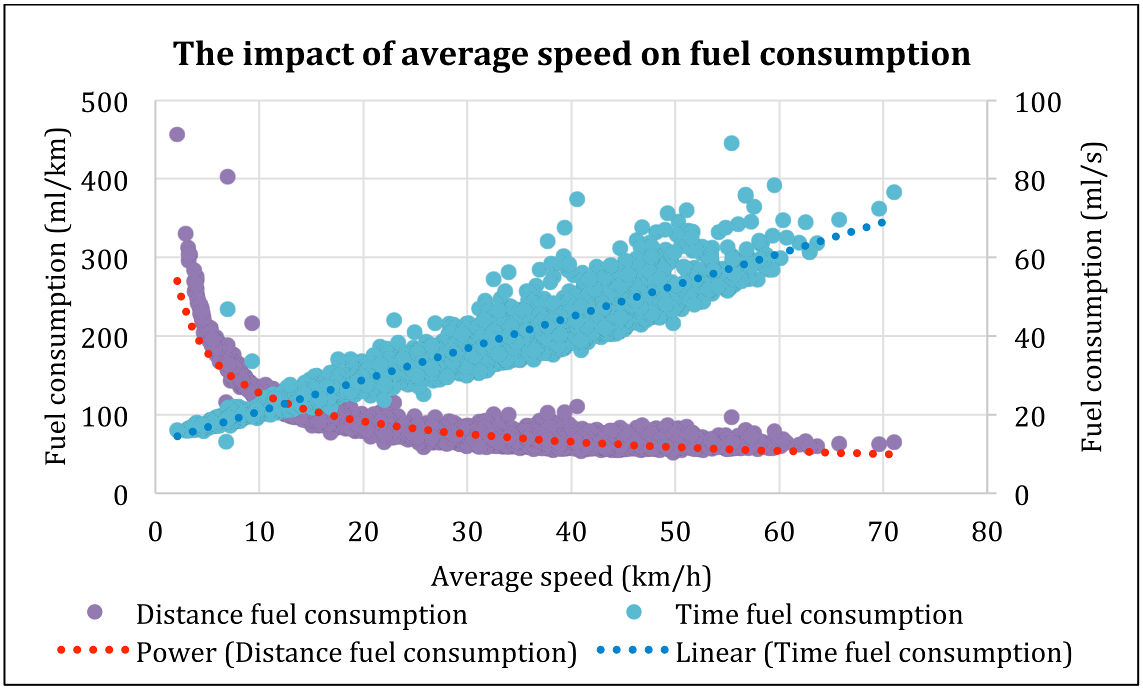


Figure 4.4: The impact of average speed on fuel consumption based on all the collected speed data

Up to here the variables, that are discussed previously, have a linear relation with fuel consumption; however, in the case of speed, this relation is not linear. Therefore, the result depends on the starting point for evaluation. To overcome this problem, the results are first classified in 10 ranges (same as the other variables). Then, the differences between two neighbouring categories are calculated (in percentage). At the end, the average percentage variation is calculated.

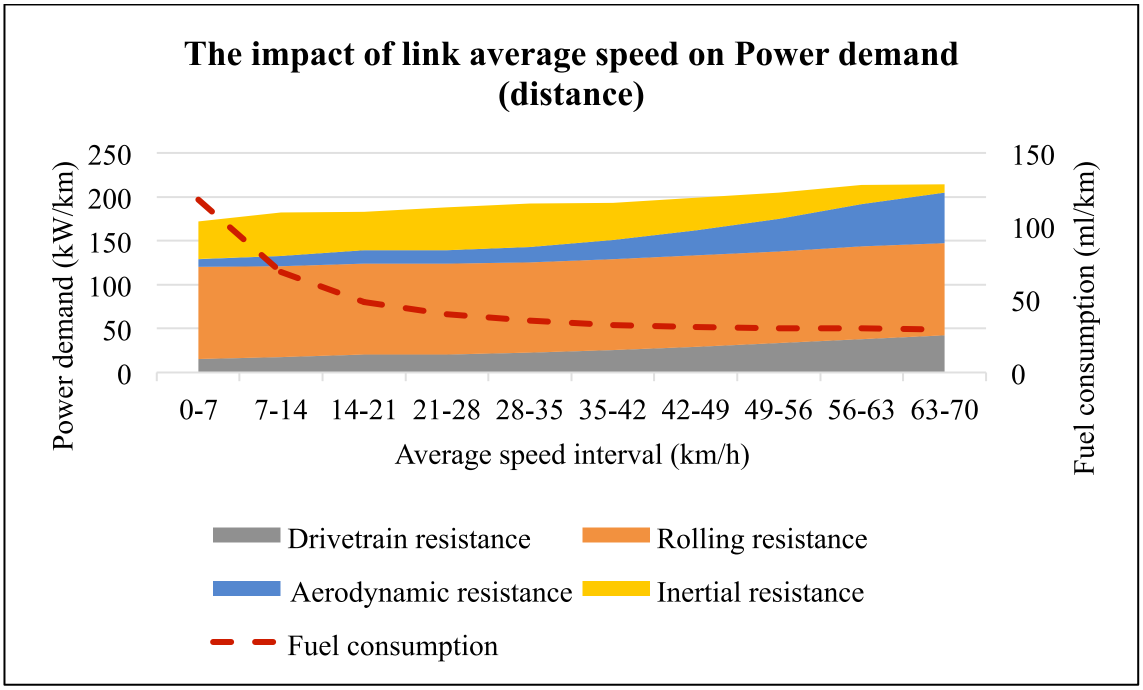


Figure 4.5: The impact of speed on power demand and fuel consumption

As a result an average of 13% change in fuel consumption is observed by a 10% change in speed. It is however important to note that the distribution of speed across different categories is not the same. For example, if the average speed of a link with heavy traffic is improved, firstly the impact on fuel consumption is more significant in low speed and secondly more vehicles will be affected. Also, the acceleration rate can have a significant influence on vehicle emissions. For example, Figure 4.6 demonstrates two different speed profiles in our dataset with the same average speed but different driving behaviours. In this case, profile 1 resulted in 7% less fuel consumption, comparing to profile 2. In this analysis, the impact of acceleration will not be discussed separately.

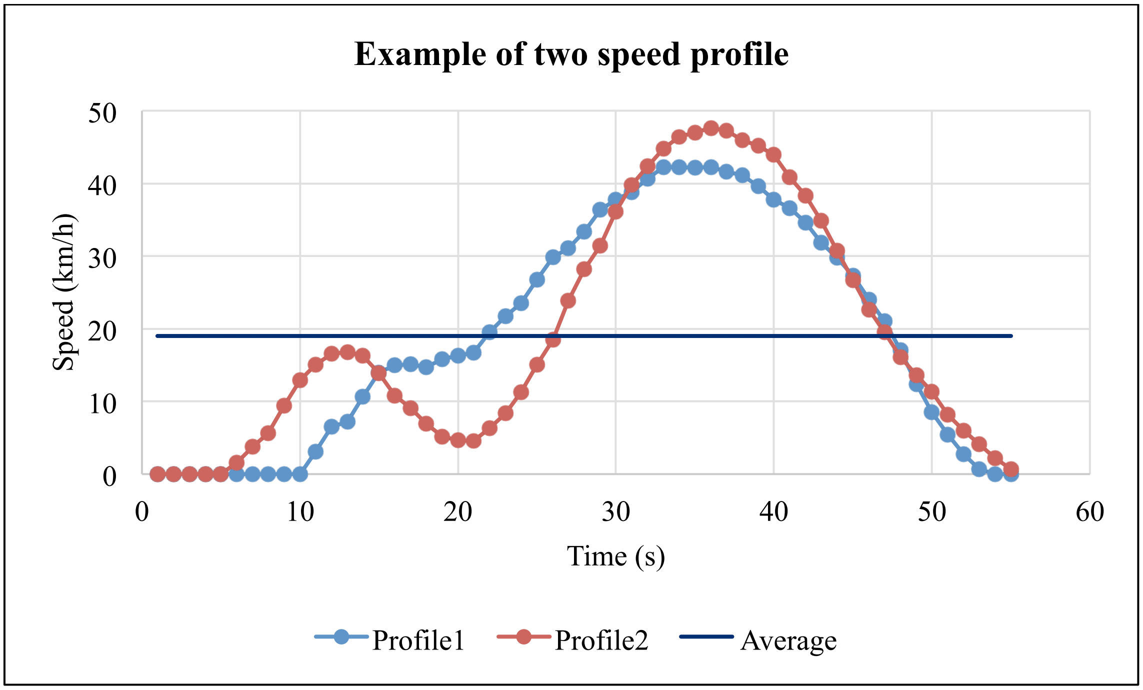


Figure 4.6: The impact of acceleration profile on fuel consumption

4.2.3 Ambient condition

In this study the ambient condition refers to temperature and wind speed. The temperature can affect the fuel consumption in two modes: cold start and the AC. In cold climates, such as in Quebec, the temperature can drop to -30°C, which makes the impact of cold start more significant than in warmer regions where that might not be the case. The excess fuel consumption of an average recent car for the first kilometer can be as high as 32 ml in -30 °C, while it goes down to about 6 ml in +30°C conditions. Of course, the extra fuel consumption decreases for the following kilometers as the engine warms up, shortening the gap between warm climate and cold climate. For an average 10 km urban trip, the total excess fuel consumption is about 173 ml in -30°C and 45 ml in +30°C. Depending on the temperature, the cold start can increase the fuel consumption by up to two times for an entire trip. The relation between temperature and excess fuel consumption is also not entirely linear; on average, every 10% drop in temperature (6°C) can increase the fuel consumption by 15%.

On the other hand, in warmer weather, the AC factor also has a significant impact on fuel consumption. Contrarily to the cold start, the impact of AC is present at all times. On a sunny day the AC can result in 160% more fuel consumption (in 30°C). On average for every 6°C increase in the temperature, the fuel consumption is increased by about 79%, 13%, 96%, and 12% for urban shade, highway shade, urban sunny, and highway sunny conditions respectively. Considering the proportion of shade and sun being the same, and urban driving accounting for 55% and highway for 45% (Natural Resource Canada, 2012), the total average impact of AC is about 54% for temperatures above 6°C. To understand the impact of temperature while considering both AC and cold start, Figure 4.7 demonstrates the accumulated impact on fuel consumption. As we can see depending on the road type, the comparative impact can differ. For instance, in highway driving, the impact of the cold can be more significant than the impact of the heat.

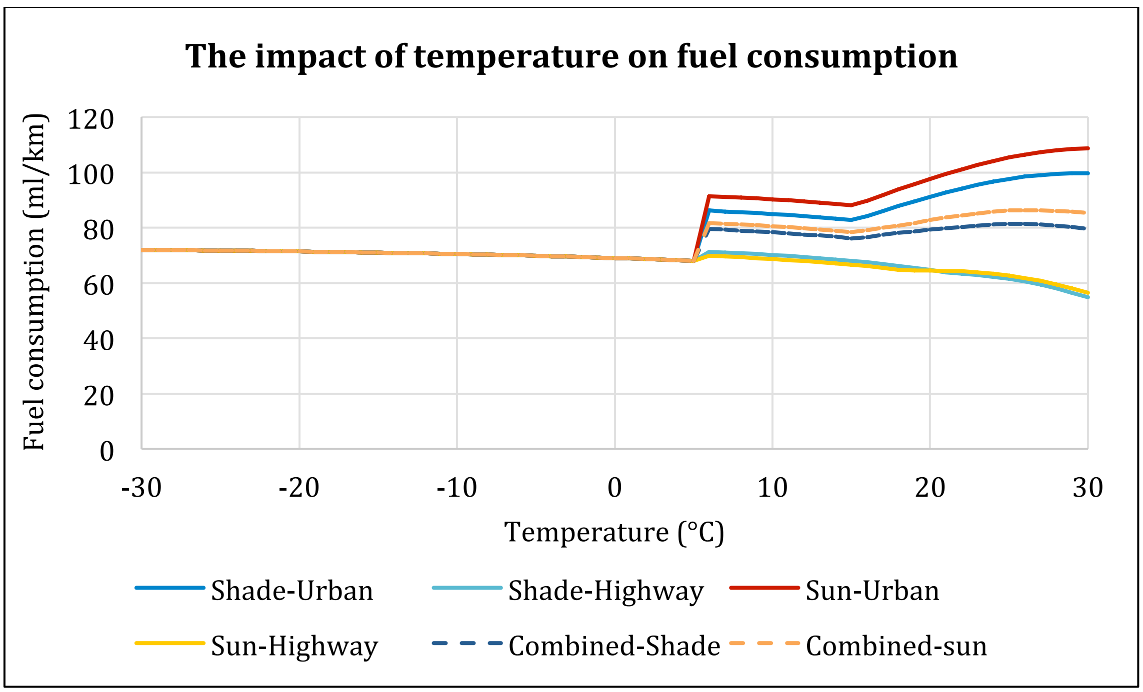


Figure 4.7: The impact of temperature on fuel consumption

The other factor in the ambient condition category is the wind speed. The impact of wind speed can be difficult to calculate; since it largely depends on the direction it is blowing. For example a headwind increases the aerodynamic drag and therefore the fuel consumption, whereas the tailwind can reduce the fuel consumption by acting as an extra kinetic force helping the vehicle to move forward. In this study only the impact of direct headwind is evaluated. To determine the range of the wind, the maximum wind speed in Montreal is selected using the historical weather data. Based on the analysis, on average, a 10% change in wind speed (6 km/h) can increase the fuel consumption by about 7%. As we can see in Figure 4.8, the impact is more significant at higher speeds.

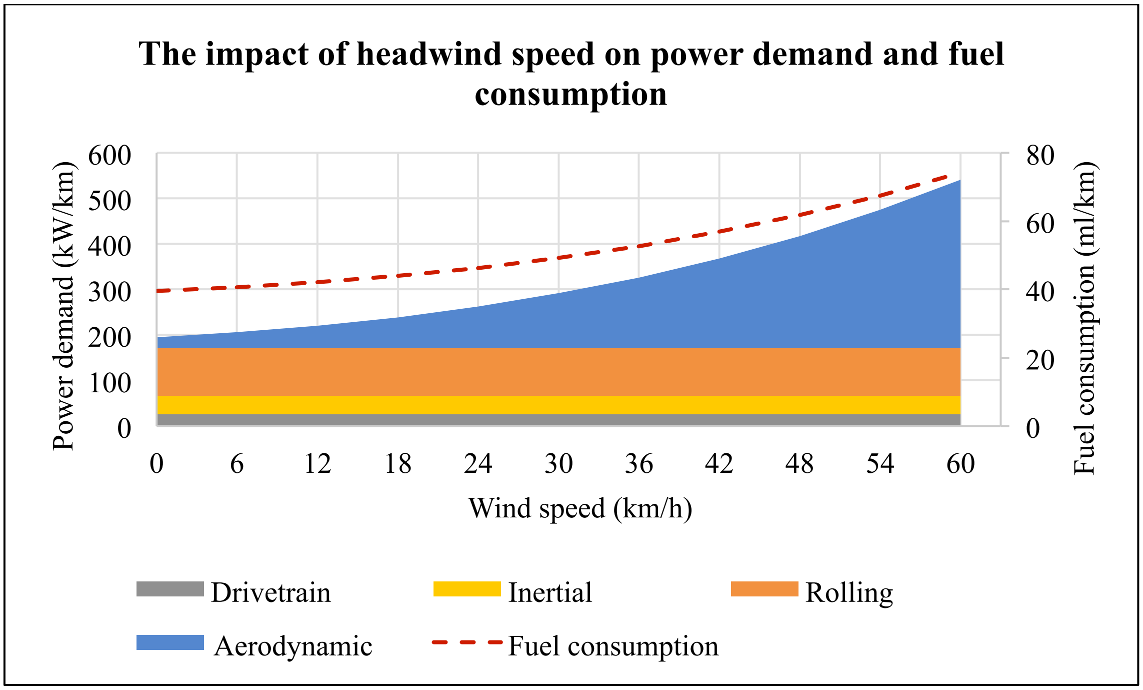


Figure 4.8: The impact of wind speed on power demand and fuel consumption

4.2.4 Road characteristics

In this study two aspects of the road are evaluated: the road grade and the road texture (which influences the rolling resistance). In urban planning references, the maximum road grade is recommended to be 8%, or about a 5 degrees slope. Based on the analysis, the road grade affects the inertial resistance. The correlation between the road grade and fuel consumption is also not linear; on average, a 0.8% change in road grade (10% change in the whole range) can increase the fuel consumption by 5%. The impact is more significant on steeper roads.

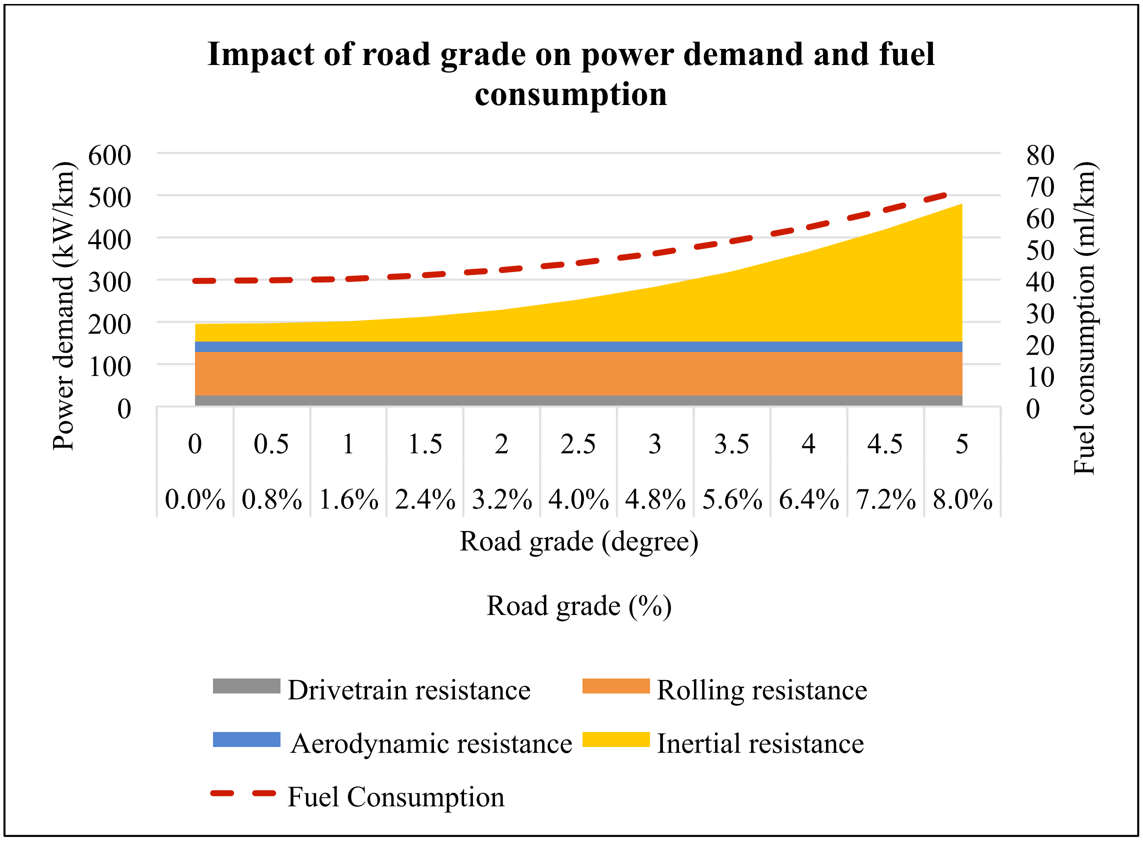


Figure 4.9: The impact of road grade on power demand and fuel consumption

The last factor to analyze is the impact of the road surface. However for that matter, as discussed in the methodology, another method is taken into consideration. Considering the range of International Roughness Index (IRI) between 1 and 4 mm, and the Mean Profile Depth (MPD) between 0.5 and 1.5 mm, the range of rolling resistance is calculated by increasing both measures at the same time. As a result, through a 10% increase in these values the rolling resistance increased by 2%. Applying the 2% difference in the initial value, the total average fuel consumption was increased by 0.5%.

4.3 Cross analysis

Up to this part, each of the variables were analysed separately but in the real world often few variable change at the same time. To understand how much fuel consumed in different situation two scenarios will be compared. One with the highest fuel efficiency and the other is the least fuel-efficient. Any other situation will be something between the two values.

The first scenario is the baseline scenario, where all the variables are set that result in the least fuel consumption. In this condition, the vehicle weight is 800 and engine capacity 1 L, the vehicle is the most aerodynamic with the highest engine efficiency. Regarding the environment and network characteristics, the temperature is 5°C and cloudy with no wind and there is no elevation on the entire trip. Also, for the speed profile, an average on the entire dataset is used. Based on this condition the fuel consumption of 1 km trip is about 68 ml.

On the other hand, it is the worst-case scenario, where all the variables are at their least fuel-efficient condition. In this scenario, the vehicle weight is 2800 with 6 L engine and lower efficiency also the vehicle is the least aerodynamic. The temperature is 30°C, with wind speed of 60 km/h and 5 degrees of road elevation. In this scenario the fuel consumption increases up to 920 ml, about 13 times more than the economic scenario. It is important to mention that not all of these conditions are constant in the real world.

However, these two scenarios are extreme conditions that do not happen very often in the real world and are used to demonstrate the range of variation. Therefore, to understand more realistic situations, a set of realistic scenarios were evaluated.

For the realistic scenarios, two bestselling vehicles of 2015 in Canada for two different classes were selected (based on the autotrader.com): Honda Civic and Ford Escape. Also, for these two vehicles 3 different temperatures were chosen: a cold sunny day (-30°C), a mild cloudy day (+15°C), and a hot sunny day (+30°C). Table 4.3 summarises the fuel consumption for both Honda Civic and Ford Escape in these situations. As we can see, the Ford Escapes consumes about 20% more than the Honda civic. However, the relation is not linear and it varies according to the situation. The highest difference is for cold temperatures.

Table 4.3: Honda Civic and Ford Escape fuel consumption

	Civic	Escape
Sunny -30	105.6	128.07
Cloudy 15	109.8	132.2
Sunny 30	118.8	141.2

4.4 Conclusion

Regarding the comparative analysis of the factors that affect vehicle fuel consumption, several factors should be taken into consideration: the range of variation and the fact that it can be different in different regions, the distribution of the situation, and the impact of the variable alone on fuel consumption. In our analysis, the first two aspects are taken into consideration; however, the distribution of different conditions is not considered, in order to be able to demonstrate the influence of the factors regardless of the activity. In the results, the impact of each factor on fuel consumption is evaluated. But which variable has a higher influence on fuel consumption?

Table 4.4: The average impact of 10% variation of each variable on fuel consumption

Variables	**% Change**
AC	55
Engine capacity (litre)	25
Cold start	15
Average link speed	13
Vehicle weight (kg)	11
Wind speed (km/h)	7
Engine efficiency factor (ml/kW)	6
Road grade (degree)	5
CdA	3
IRI and MPD	0.5

Table 4.4 summarizes the impact of each variable on fuel consumption. In this table, the impact of a 10% change in each variable on the total fuel consumption is calculated, then the average value is calculated (for non-linear variations). As can be seen, air conditioning is the most significant factor. It is important to note that the impact of air conditioning is only considered for the range of temperatures where air conditioning is

typically used. When the impact of air conditioning is estimated for all temperatures (-30, +30), the percentage of change reduces to 24%; but it is then a less plausible situation. Engine capacity, cold start, average link speed, and vehicle weight also have the highest influence, in this order. It is sometimes argued that some factors such as the road grade and the wind speed can be gathered together as one subgroup. For instance, regarding the road grade, vehicles usually start from a certain location and at the end of the day return to the same location with the same altitude. However, in the analysis we saw that the impact of the road grade is not linear and the road grade distribution is not necessarily the same for the trip back. Also, some emissions are sensitive to time, meaning that the concentration of certain emissions in one location can result in major health issues.

In addition, the impact of some variables is usually overlooked in the emissions estimation. One example is the cold start. The relation between the temperature and the excess cold start is not linear which makes it erroneous to use the average temperature for cold start estimations. However, in some models such as MOVES the average hourly temperature during a month is used. Such details being discovered in the results make it easier for the practitioners to be aware of such mistakes, as well as confirming the importance of reliable databases.

As an outcome of this review and analysis, a tool was developed in Microsoft Excel environment to illustrate de variability of estimations. The calculation behind the tool is the same as the one presented in this study. This tool was developed to facilitate the evaluation of different factors on fuel consumption and CO_2 emissions. This tool is capable of calculating fuel consumption for pre-defined speed profiles as well as any other speed profiles. Figure 4.10, demonstrates this tool; a complete documentation, covering the equations and method of calculation, is also provided within the tool.

Figure 4.10: The fuel consumption tool developed in Excel environment

It is important to mention that these analyses are based on the models available in the literature. There are some limitations to this study; such as for the cold start emissions, the model is selected from a European study, which reflects the European fleet characteristics. However, regarding the fuel consumption with more recent vehicles, the difference might not be significant, yet this is open to further investigation. Unfortunately, a similar model for North America was not available. Another limitation of this study is the unavailability of the fuel consumption data in order to compare with the calculated values.

As a complimentary to this study, the sensitivity analysis of the MOVES emissions model is conducted in the following section. The analysis will cover both activity distribution and variations of certain variables (databases). The two analyses, side by side, can reveal some of the differences between the two approaches.

CHAPTER 5 MOVES SENSITIVITY ANALYSIS

As discussed before, there are various tools and models available to estimate emissions all around the world. Regions can have different characteristics, fleet compositions, and environments, and require adapted methodologies or models. In North America alone, there are many models available. The three main models that are most dominant are: CMEM in California, VT-Micro in Virginia, and MOVES in the rest of the U.S. and Canada.

As presented in the literature review, the MOtor Vehicle Emissions Simulator (MOVES) is able to estimate pollutants, greenhouse gas emissions, air toxics, and energy consumption from on and off-road vehicles. This model can estimate the emissions at three different scales: national, county, and project; as well as two modes: emissions rate which provides disaggregated results per unit of activity, and inventory mode which calculates the total emissions on the network disaggregated by parameters such as year, month, day, vehicle type, fuel, etc.

MOVES is a very comprehensive and refined emissions model, which needs extensive input data for implementation. The accuracy of each dataset can have a significant influence on the results (Koupal, DeFries, Palacios, Fincher, & Preusse, 2014). Due to the complexity of the emissions calculation, it is crucial to understand how each factor can affect the estimations; sensitivity analyzes is the proper tool to pursue that aim.

There are many sensitivity analyzes conducted for MOVES, each focusing on certain aspects of the model. For example, Bell, Kothuri, and Figliozzi (2013) evaluated the use of the local GPS data on CO, NO_X, PM, and CO_2 emissions estimations for trucks. In their study, they discovered that speed, road grade, and weight have significant influence on emissions, CO_2 emissions being most sensitive to grade and weight in congested conditions and PM emissions most sensitive to speed.

Also, in another study, Koupal et al. (2014), in a larger scale, compared the data provided to National Emission Inventory by state/local/tribal agencies and compare with the EPA's best practice guidance. In their analysis, they found a significant gap between the two. Evidently, this gap is highly influenced by the input datasets provided by the agencies. Their analysis reflects the sensitivity of the input data on HC, CO, NO_X, and PM for different vehicle type.

In addition, Choi, Beardsley, Brzezinski, Koupal, and Warila (2011) in another study, examined the impact of temperature and humidity on THC, CO, NO_X, and $PM_{2.5}$. They confirmed that the temperature has a substantial impact on MOVES emissions estimations, specifically in cold temperatures.

Also in a report provided by the U.S. Department of Transportation, a comprehensive sensitivity analysis of the model is provided, covering temperature, humidity, ramp fraction, analysis year, age distribution, and average speed distribution (Noel & Wayson, 2012). In their analysis they focused on the main pollutants (CO, NO_X, $PM_{2.5}$, and VOC) for different vehicle types.

In Texas Also, the Texas Department of Transportation conducted a sensitivity analysis, on various factors including control program input, temperature, humidity, barometric air pressure, vehicle type distribution, fleet age distribution, vehicle speed, etc. The gases that were evaluated were VOC, CO, NO_X, CO_2, PM_{10}, and $PM_{2.5}$. Regarding the temperature, they defined four different scenarios: normal summer day, cold summer day, normal winter day, and warm winter day and calculate the emissions for each of these scenarios. Also, the impacts of vehicle characteristics were evaluated by comparing the vehicle age and VMT of different years on the emissions. In this study, they also demonstrated the impact of speed by illustrating the vehicle emissions in different speed ranges.

Furthermore, Vallamsundar and Lin (2013) evaluated the impact of change of speed, temperature, seasons, time of day and year on $PM_{2.5}$ comparing the results to another emissions model (AEROMOD). They also confirmed that MOVES is highly sensitive to speed data input as well as temperature.

As we can see there are extensive sensitivity analysis on MOVES; however, none of these studies discussed which factor has the highest influence. This study, with the comparative analysis, aims to characterize the impact of different factors on CO_2 emissions as calculated by MOVES. The results will help decision makers in two ways: first, it gives a better picture of the impact of data comprehensiveness and accuracy and the extent of the differences (or error) it can induce, which is the primary and critical step in any decision making. Secondly, the results will facilitate the evaluation of different strategies in terms of emissions, by providing a comprehensive overview of the variables and their impacts on emissions. In previous sensitivity analyses, it has been discussed that temperature, humidity, age, speed, and ramp fraction are the most sensible factors; however it is not demonstrated that which factor is more sensitive to change. Therefore, in this study we will discuss these parameters to verify their comparative sensitivity regarding the estimation of CO_2 emissions.

5.1 Methodology

To estimate the emissions from transportation, the Quebec Ministry of Transportation (MTQ) has recently replaced MOBILE6C (the previous transportation emissions estimation model) with MOVES. The AECOM Company assisted MTQ through this migration process. The Quebec version of MOVES is called Motrem[11]-MOVES, which is a user-interface built into the Microsoft Excel environment, which enables the user to retrieve different sets of data such as traffic related data (the outputs from EMME software), meteorological data, fuel characteristics, fleet composition, etc. This interface converts the available datasets to be compatible with MOVES County Data Manager (CDM) format. The user-interface is also capable of running MOVES in the same environment without leaving the application.

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[11] Abbreviation for the urban transportation model for the Montreal region

Figure 5.1 is the schematic representation of Motrem-MOVES. The orange ellipses are the three main phases: the PreMOVES phase retrieves and prepares the data from external databases for MOVES, the MOVES execution phase that interacts directly with MOVES imports the modified data and runs the model, and finally, the PostMOVES phase displays and summarizes the results. In this study, the input datasets are collected after running the PreMOVES phase and are imported manually in the original MOVE software (version MOVES10b) through the CDM to be able to do the data manipulation. The software is then run at county-level inventory mode.

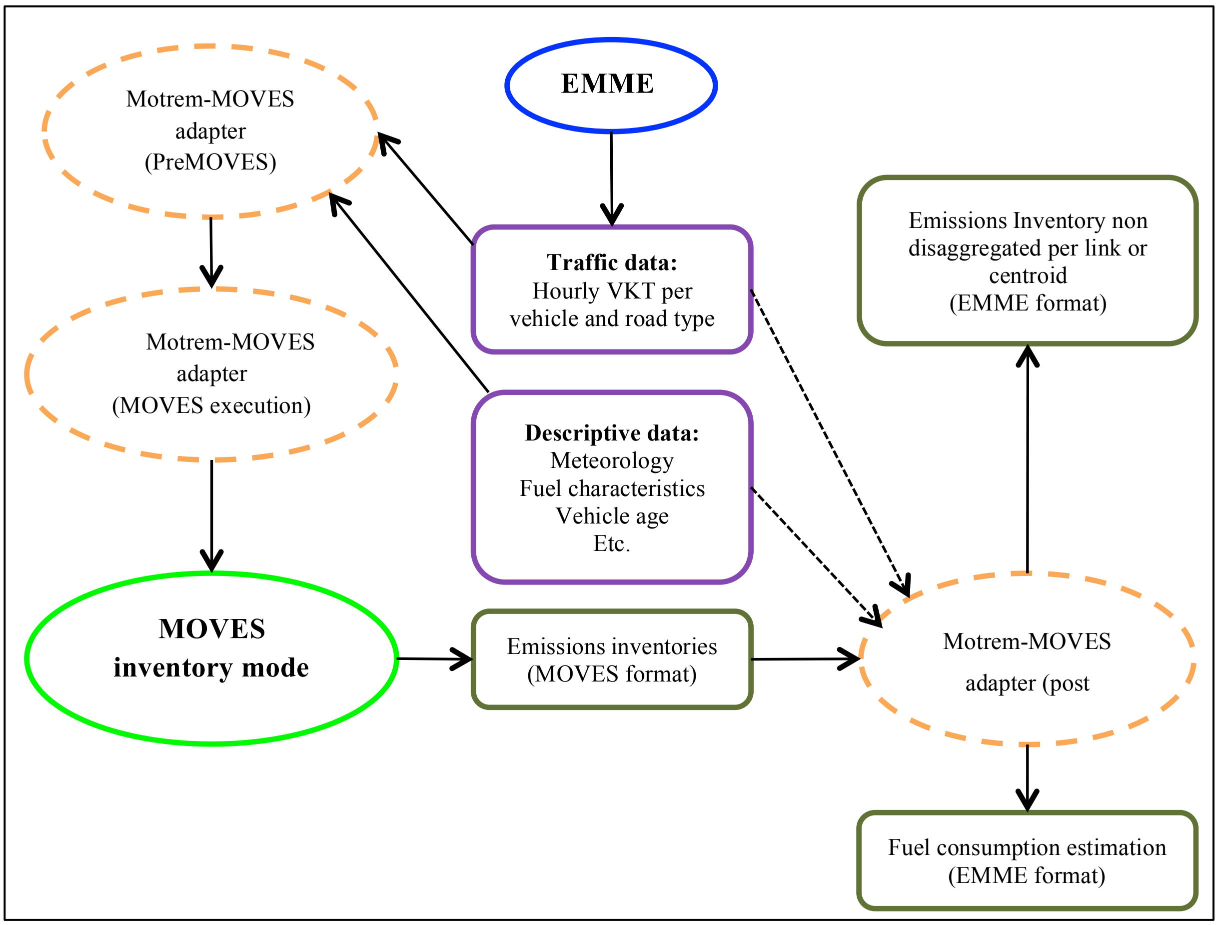

Figure 5.1: General schematic representation of Motrem-MOVES in inventory mode (Bourget, 2013)

In this analysis, a local sensitivity analysis was conducted by changing one variable at a time. The analysis covers different factors: average speed, age distribution, temperature, humidity, and ramp fraction. After a change in each variable, the results are then compared to the baseline scenario. The baseline scenario represents an average weekday in November 2011. The average daily temperature is 3°C and the hourly temperature and humidity are shown in Figure 5.2. Also, Figure 5.3 and Figure 5.4 provide some statistics of the number of vehicles and kilometers traveled that are used as the input dataset in our analysis. It is important to note that in our analysis we are focused on the CO_2 emissions from gasoline passenger vehicles.

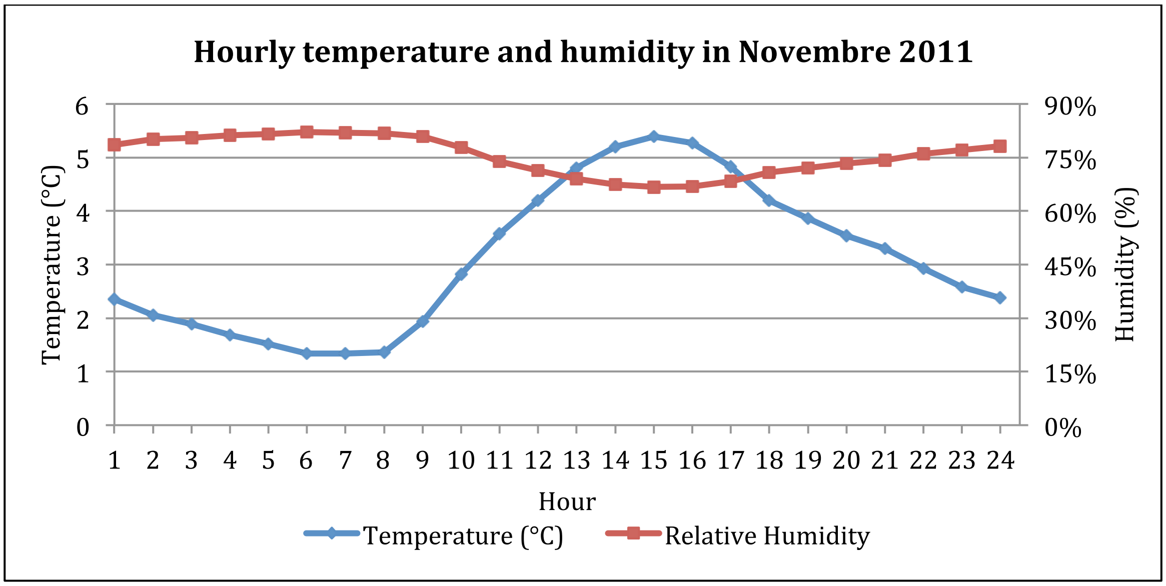

Figure 5.2: Hourly temperature and humidity used in the baseline scenario based on the data provided by MTQ as a part of Motrem MOVES dataset

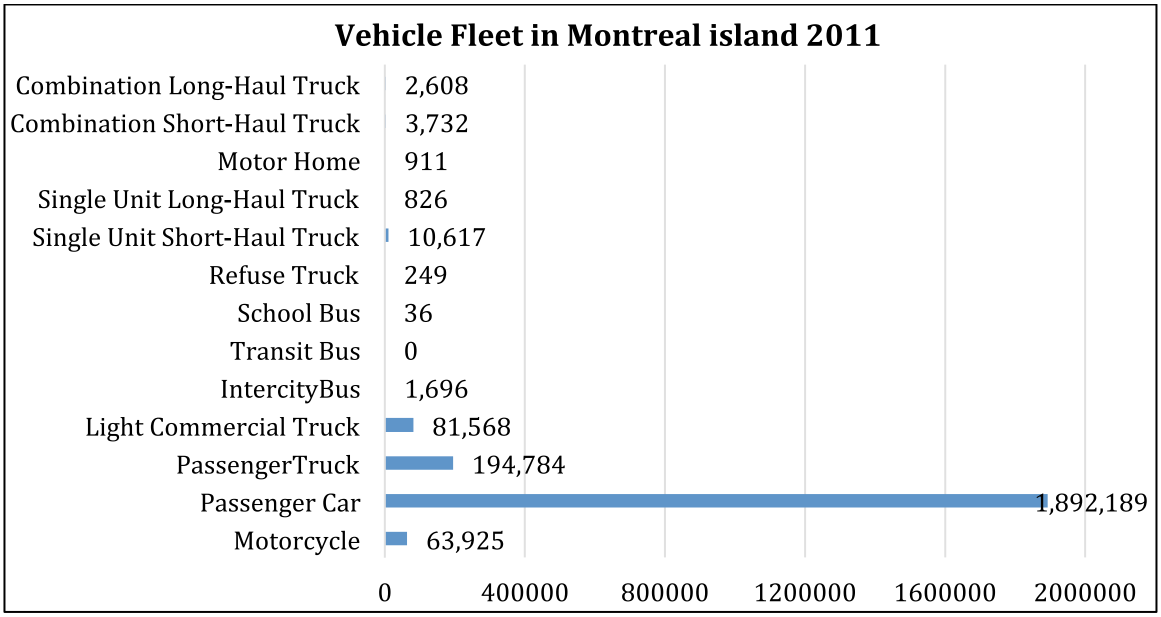

Figure 5.3: Vehicle fleet in Montreal Island in 2011 based on the data provided by MTQ as a part of Motrem MOVES dataset

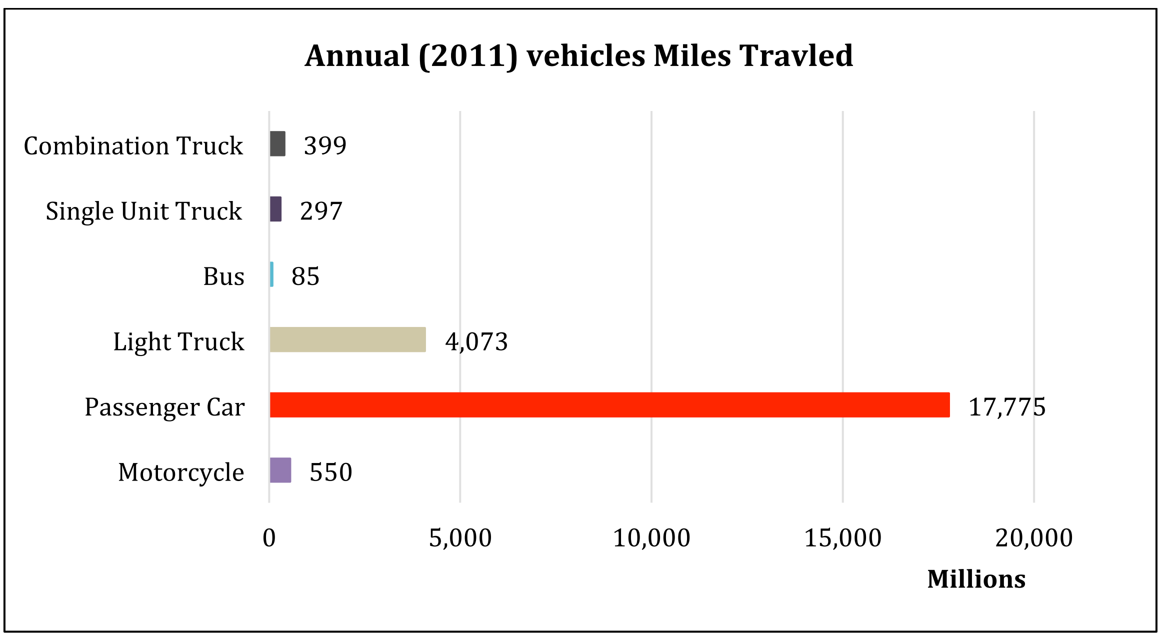

Figure 5.4: Total vehicle miles traveled based on the vehicle category on the Island of Montreal in 2011, the data is provided by MTQ as a part of Motrem MOVES dataset

In this section we faced a methodological challenge: the nature of the datasets was not similar. In the MOVES input dataset, the speed data is imported in terms of frequency of VSP. That is for each hour of the day a distribution of Vehicle Kilometres Traveled

(VKT) across different Vehicle Specific Power (VSP) range is required by the model to calculate emissions; same applies to the age distribution. However, in case of temperature, humidity and ramp fraction the values corresponding to each variable is required and not the distribution. Therefore, we had to adopt different methods for sensitivity analysis of each of the datasets. The details of the methods are explained in this section (Government of Canada, 2015).

As confirmed in different studies, speed profile is considered one of the most important factors in emissions estimations (André & Hammarström, 2000). MOVES emissions calculations are based on speed "patterns" for each ranges of speed (referred as the speed bins). A speedbin is chosen and affected to each road link, according to the corresponding modeled speed (Table 5.1). Each speedbin, sourcetype, and roadtype combination is associated with a specific driving cycle. There are 5 types of road in MOVES: off-network, rural restricted, rural unrestricted, urban restricted, and urban unrestricted. The off-network activity is not considered in this study.

Table 5.1: Definition of speed bins

SpeedBin ID	Speed range (mph)	Speed range (km/h)
1	$v < 2.5$	$v < 4.0$
2	$2.5 \leq v < 7.5$	$4.0 \leq v < 12.1$
3	$7.5 \leq v < 12.5$	$12.1 \leq v < 20.1$
4	$12.5 \leq v < 17.5$	$20.1 \leq v < 28.2$
5	$17.5 \leq v < 22.5$	$28.2 \leq v < 36.2$
6	$22.5 \leq v < 27.5$	$36.2 \leq v < 44.3$
7	$27.5 \leq v < 32.5$	$44.3 \leq v < 52.3$
8	$32.5 \leq v < 37.5$	$52.3 \leq v < 60.4$
9	$37.5 \leq v < 42.5$	$60.4 \leq v < 68.4$
10	$42.5 \leq v < 47.5$	$68.4 \leq v < 76.4$
11	$47.5 \leq v < 52.5$	$76.4 \leq v < 84.5$
12	$52.5 \leq v < 57.5$	$84.5 \leq v < 92.5$
13	$57.5 \leq v < 62.5$	$92.5 \leq v < 100.6$
14	$62.5 \leq v < 67.5$	$100.6 \leq v < 108.6$
15	$67.5 \leq v < 72.5$	$108.6 \leq v < 116.7$
16	$72.5 \leq v$	$116.7 \leq v$

To analyse the impact of speed on emissions one approach is to set the distribution of a specific speedbin to 1 (100%) and the rest of the bins to 0. However, this approach could not reflect the real proportion of speedbins. To resolve this issue, a novel approach was implemented. Based on this approach, in the first step, the average speed for each hour of the day was calculated, as well as the emissions corresponding to the speed (Figure 5.5).

The second step is the redistribution of speeds to analyse its impact on emissions. To do so, we selected the median regarding the distribution. Then we divided the speed ranges in two categories, the low emissions category, ranging from speedbin 7 to 14, and the high emissions category, which are the rest of the speedbins. To redistribute the speed, we first examined the distribution to determine if it follows any specific distribution (such as standard, Gaussian, etc.), however, we could not find any specific distribution. Therefore, the proportional approach was taken where a certain percentage of one category were reduced and added to the other category proportionally. Based on this method each 10% change in the speed distribution changed the total average speed by less than 1 km/h.

The other dataset necessary to calculate emissions is the age distribution. For this sensitivity analysis, vehicles have been classified in two main categories: less than 10 years old, and 11 years and older. In the baseline scenario, 64% of the vehicles are less than 10 years old. For the sensitivity analysis, the same approach as in the speed distribution was applied. In total four different scenarios were investigated: in the first two scenarios, 5 and 10 percent of the vehicles have been removed from the 11 years and above category and added to the less than 10 years. For the two other scenarios, the same percentages were moved from the younger vehicle group to the older one (resp. -5 and -10% in Figure 5.6).

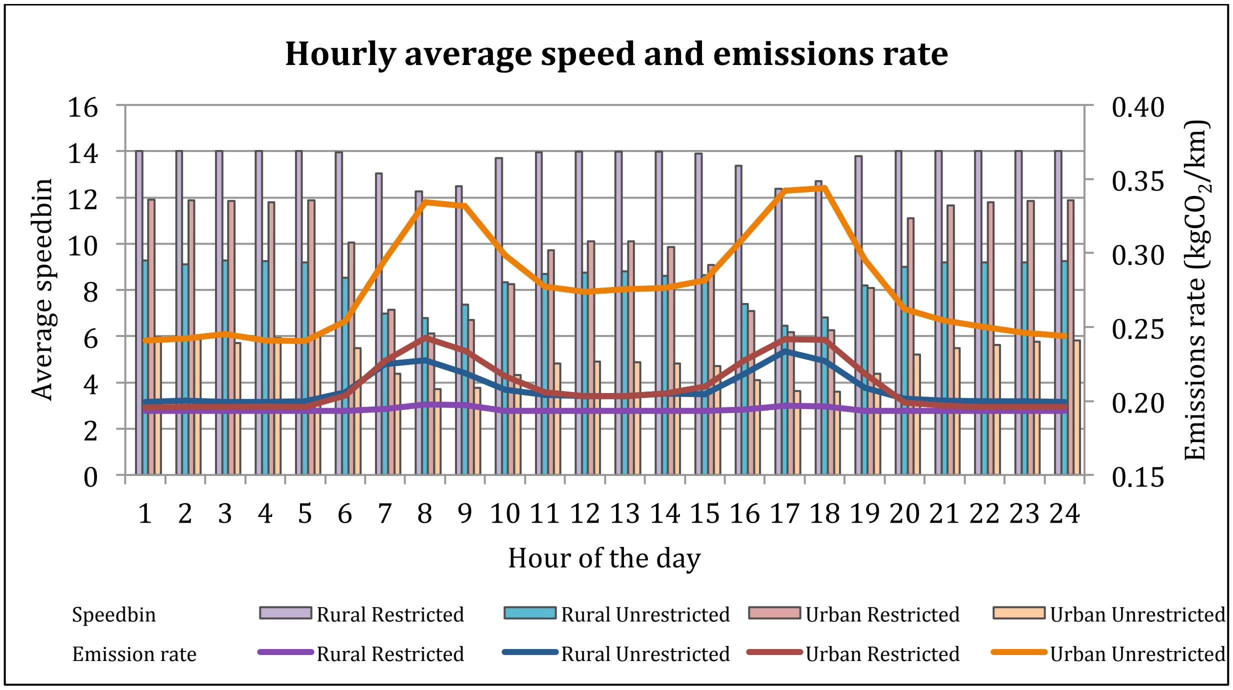

Figure 5.5: CO_2 emissions sensitivity to speed distribution for running and start exhaust emissions based on the data provided by MTQ as a part of Motrem MOVES dataset

Between the 5 scenarios, the average age varies from 6.7 to 8.6 years old when the redistribution changes from +10% to -10%. It is important to note that the age distribution is directly combined with vehicle activity (VKT and number of starts). The results of this analysis can provide a better picture of the impact of fleet age and the activity profile dataset on the estimations.

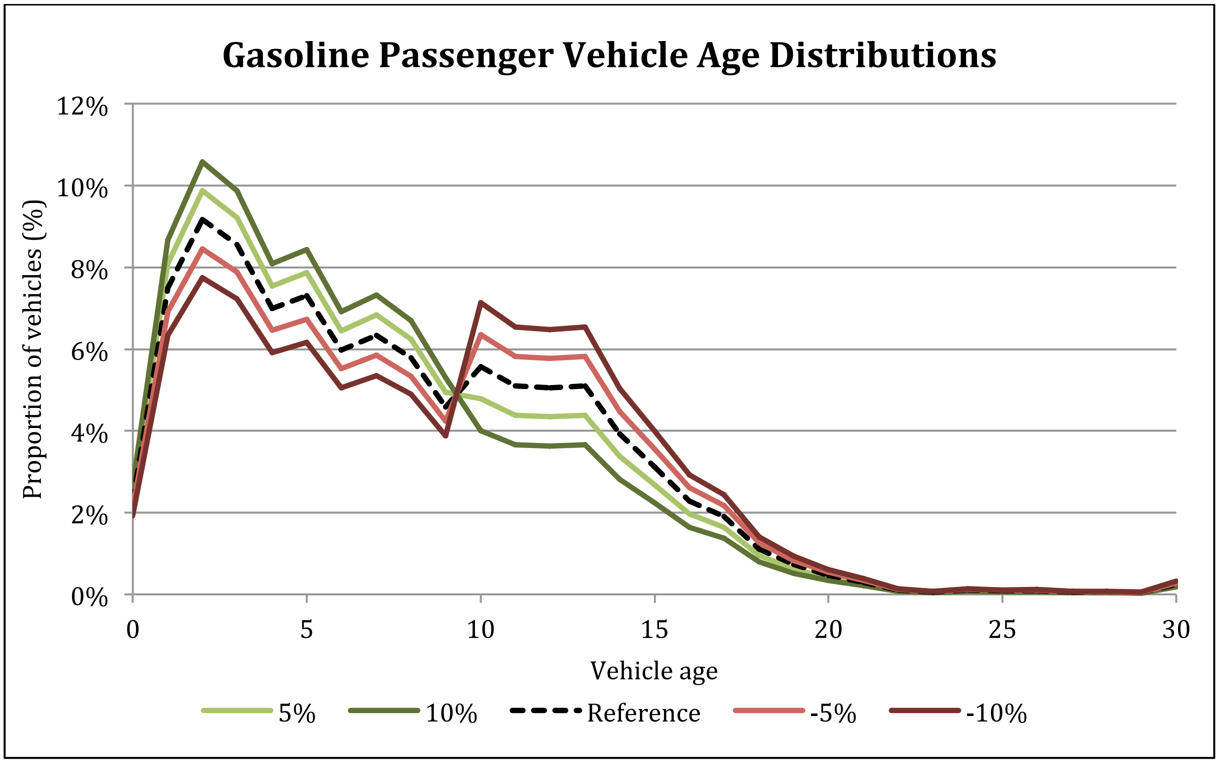

Figure 5.6: Gasoline passenger vehicle age distributions for the baseline and modified scenarios based on the data provided by MTQ as a part of Motrem MOVES dataset

The next variable is the ambient condition. Specifically in Montreal, the weather can vary between -30 to +30°C throughout the year (Figure 3.8). To analyze the sensitivity of the model, we varied the temperature between -30 to +30°C by 10 degrees increments. To achieve a more realistic representation of the Montreal weather conditions, the average relative humidity (corresponding to the temperature) has been retrieved from the historical data in Environment Canada website for 2011 (Government of Canada, 2015). Table 5.2 provides the temperature and the relative humidity used for this analysis. In our scenarios the temperature is constant throughout the day. The temperature can affect the emissions in two ways: in very cold temperatures the start exhaust increases drastically and in higher temperatures the use of air conditioning can again increase the emissions.

Table 5.2: The relative humidity corresponding to temperatures in modified scenarios

Temperature (°C)	**-30**	**-20**	**-10**	**0**	**+10**	**+20**	**+30**
Relative humidity corresponding to the temperature	61%	65%	69%	72%	71%	68%	57%

The other ambient factor is the humidity. For the sensitivity analysis, the relative humidity was changed from 0% to 100% with a 10% increment while the hourly temperatures were not modified from the baseline scenario.

Also ramp fraction is one of the input dataset essential for emissions estimations. In MOVES, ramp fraction represents the time spent on the access ramps of a specific road type (USEPA, 2012). There is a driving cycle dedicated to ramps. In the initial Montreal data, the ramp fraction is set to zero. The actual ramp fraction in Montreal varies between 4 and 5 percent and the default MOVES ramp fraction is 8%. For this analysis the ramp fraction ranges from 0 to 8% with 1 percent increments.

5.2 Results

As explained before, the light-duty gasoline passenger cars represent the main part of the traffic; therefore, the analysis is limited to this class of vehicle and concerns only atmospheric CO_2 emissions. The results are derived from the inventory mode and reflect the emissions rate in g/km for an average weekday of November 2011.

The results of the analysis confirm the previous claims that the speed is one of the most influential factors. As we can see in Figure 5.7, with the increase in average speed, the emissions reduce significantly. For example, the emissions in speedbin 4 ($20.1 \leq v < 28.2$) are about 50% more than from the speedbin 9 ($60.4 \leq v < 68.4$), which also emphasizes the significance of speed on fuel consumption and the role of traffic reduction strategies for emissions reduction.

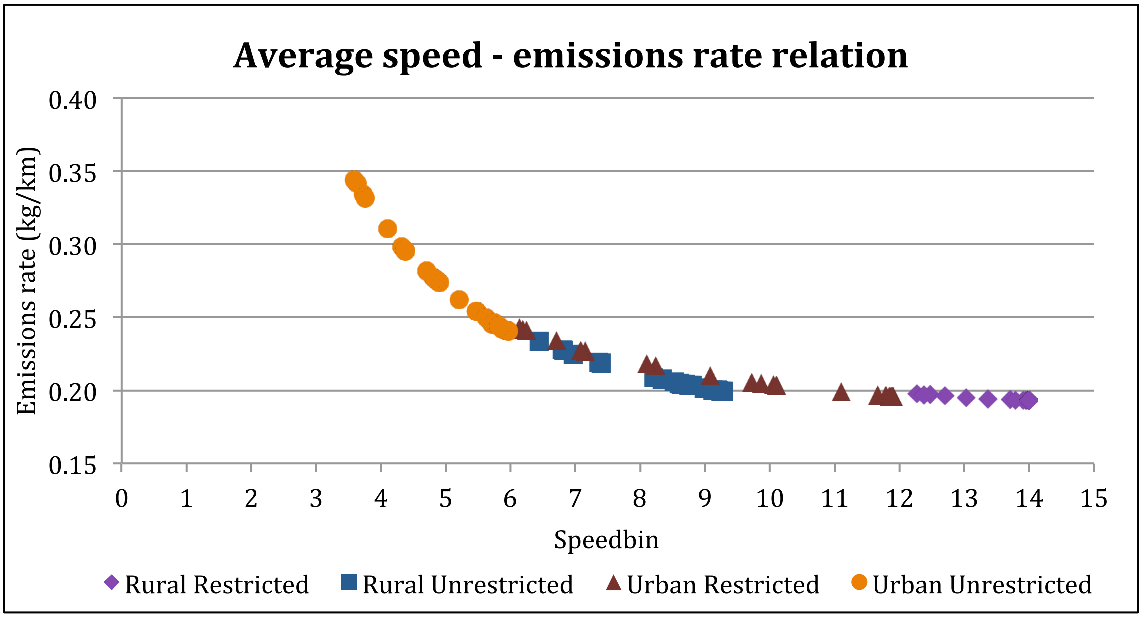

Figure 5.7: Correlation between CO_2 emissions rate and average speedbin (for the definition of speedbins refer to Table 5.1)

Regarding the age of the vehicle, it has been mentioned in the literature that it has no significant correlation with CO_2 emission; however, the estimations from MOVES did not confirm that. As we can see in Figure 5.8, there are some differences in both running exhaust and start exhaust in our scenarios compared to the baseline scenario. In case of the running exhaust emissions, the largest difference is 2% and observed between scenarios -10 and -5 (respectively the average of 8.6 and 8.1 years old). For the start exhaust emissions, the highest variation was about 5% between average ages of 8.6 and 7.2. However, it should be noted that the age distributions are inter-related with the vehicle activities. MOVES has an activity calculator within the software that calculated the number of starts based on different measures such as age of the vehicle. By default, it assumes that older vehicles take shorter trips and therefore for a certain number of VKT, the number of starts is more for older vehicle, which justifies the increase in the start emission in scenario -10. Therefore, the results of this analysis cannot explain how vehicle age can affect emission but demonstrates how the input dataset can influence the emissions calculations and how sensitive the outputs can be.

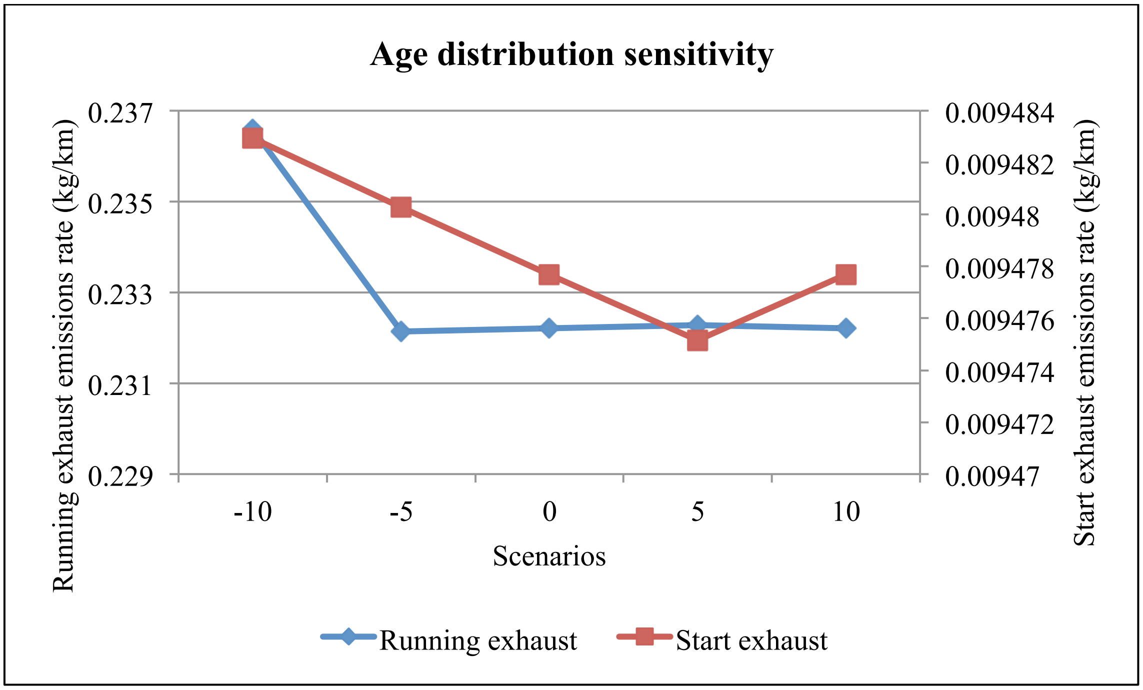

Figure 5.8: CO_2 emissions rate sensitivity to age distribution for running and start exhaust emissions

The sensitivity analysis of the temperature showed that low temperatures do not significantly affect the running exhaust emissions but can have a major influence on start exhaust emissions (Figure 5.9). The start exhaust emissions increase by a factor of 5 when temperature varies from -30 to +30°C. On the opposite, the running exhaust emissions increase by 11% at +30°C. As the overall running emissions are larger, the total emissions (Figure 5.10) increases by 1, 2, 3, 5, and 7% when the temperature decreases from 20 to 10, 0, -10, -20, and -30°C respectively. Also, the total fuel consumption increases by about 10% when the temperature increases from 20°C to +30°C.

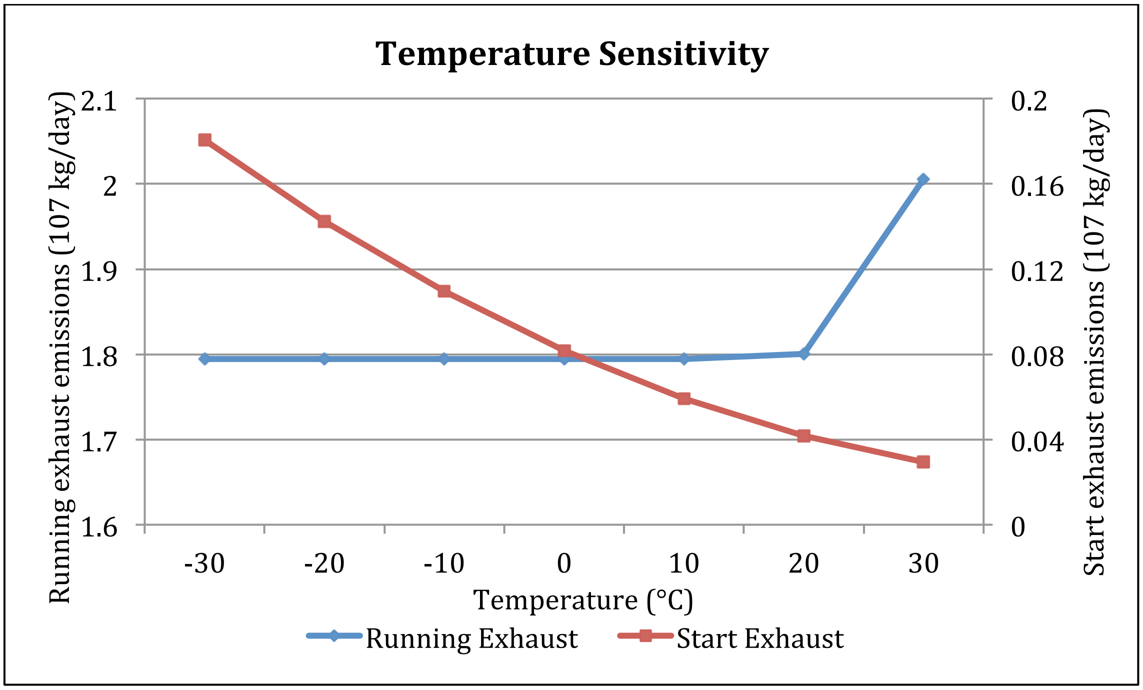

Figure 5.9 : CO_2 emissions sensitivity to temperature for running and start exhaust emissions

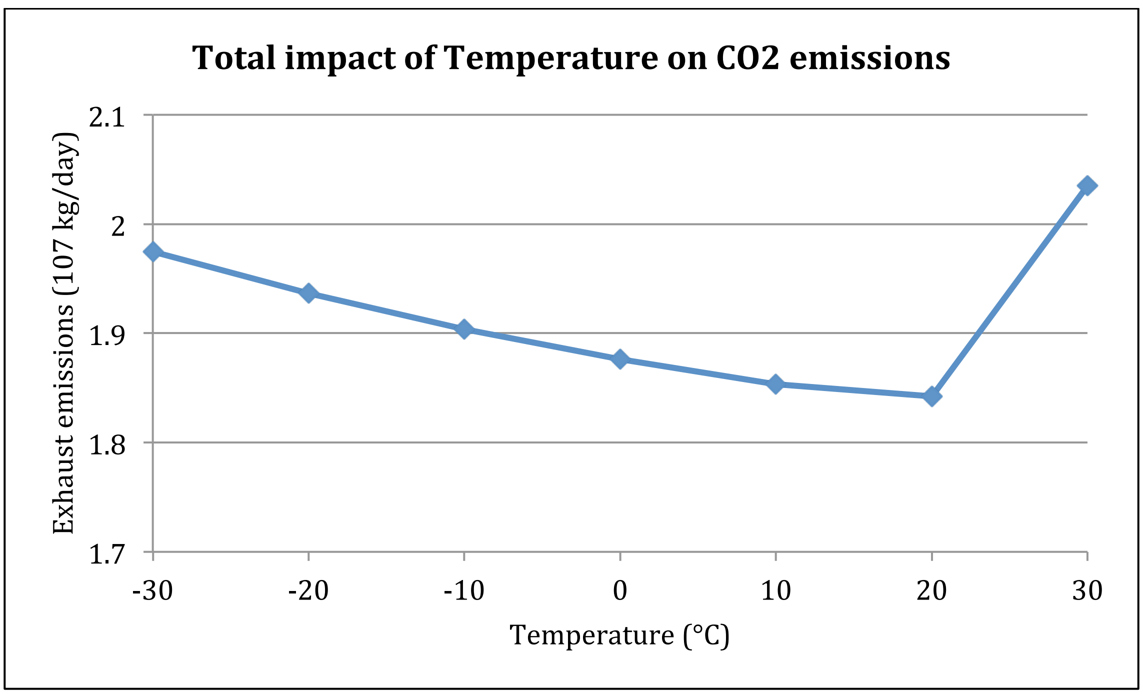

Figure 5.10: Total impact of temperature on CO_2 emissions

Also regarding the humidity, the results showed that the humidity has no impact on CO_2 emissions. However, the influence can be significant for pollutants such as CO or NO_X (Choi et al., 2011).

The last factor analysed in this section is the ramp fraction, which is found to have no influence on start exhaust emissions (Figure 5.11). On the contrary, running exhaust emissions decreases by 0.5% for each 2% increase in the ramp fraction.

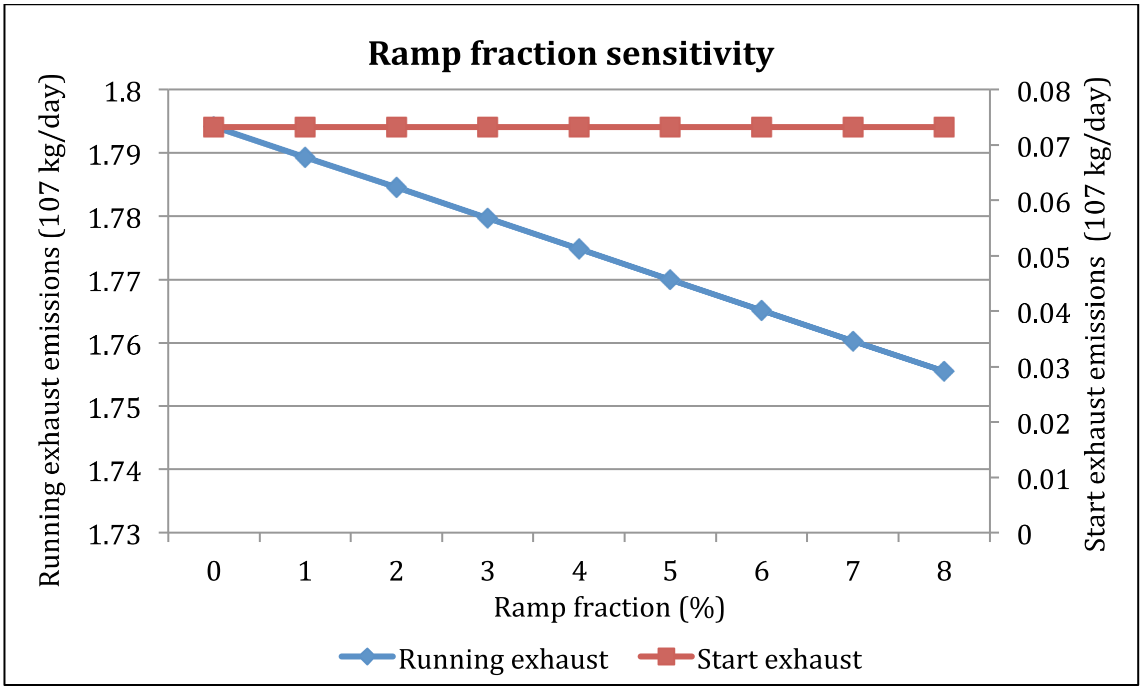

Figure 5.11: CO_2 emissions sensitivity to ramp fraction

To summarize, four variables have been discussed. In the analysis of the impact of age distribution on CO_2 emissions, we observe that the change in age distribution can affect the activity type distribution as well. Therefore, the presented results do not reflect the impact of the vehicle's age but rather the impact of change in vehicles' age distribution. Since, this variable is not independent from the others, it is not included in the comparative analysis. The other three variables studied are speed, temperature, and ramp fraction. Considering the lowest and highest range of CO_2 emissions of each of these variables, speed can have 75% impact on CO_2 emissions, temperature 11%, and ramp fraction 2%.

Based on our analysis speed and temperature had the most significant impact on CO_2 emissions; hence it is relevant to try to compare the impact of these two factors. Comparing the impact of these two factors is not easy as they are measured in different units and are very different in nature. The method that we used to compare these two variables is through modified distributions (as mentioned briefly in the methodology section). For this purpose, a low emissions category has been defined. Regarding the speed, this category is defined as speedbin 7 to 14, representing 52% of the activity. Also in the case of temperature, the range of 0-20°C is chosen, covering 54% of the hourly temperature during 2011 in Montreal. In the next step, a percentage (10-50%) of the lower emissions category was removed with respect to the current distribution and was redistributed to all the other categories in proportion to the current distribution. In other words, we tried to intensify the situation by reducing the low emissions situations by a certain percentage. Then the emissions are calculated with the new distribution, in case of speed, and value, in case of temperature.

This redistribution changed the average speed by about 1 km/h for each 10% change and about 0.1 degree for temperature. The results (Table 5.3) demonstrate that emissions are more sensitive to the distribution of speed than temperature, or in other word the accuracy of speed distribution can have higher impact on emissions. However, it still confirmed the significance of temperature on CO_2 emissions.

Table 5.3: Comparing the sensitivity of speed and temperature

	10%	**20%**	**30%**	**40%**	**50%**
Speed	0.83%	1.76%	2.80%	3.97%	5.31%
Temperature	0.58%	1.22%	1.96%	2.79%	3.75%

There are two important issues to be noted here: first, this is an average estimate and the relation between speed or temperature and emissions is not linear. Second, the distribution of the variable is not homogeneous among classes; therefore, it makes the magnitude of impact dependant on the reference point (or reference distribution). For example, the sensitivity is higher for variations occurring in lower speeds. Also, the sensitivity is weighted based on the activity and temperature distribution of Montreal and the results can be different depending on regional characteristics.

These results can benefit two perspectives:

- Firstly, for variables that cannot be easily changed (that are more structural or exogenous), the analysis demonstrates the magnitude of the errors or inaccuracies related to CO_2 estimations. Variables such as temperature, humidity and ramp fraction are in this group. It is important to note that although these variables cannot be changed by nature, they can be influenced by policies such as providing indoor parking for reducing the effect of temperature or modifying the network design in the case of ramp fraction.

- Secondly, for variables that can be more easily managed in reality (using more accessible institutional levers for actions) as a result of policies implementation (for instance congestion reduction strategies or increasing / decreasing the fleet age through renewal or incentives), the sensitivity analyzes can help identify factors having of higher impacts and quantify the expected impacts. Average speed and age distribution are among such factors.

5.3 Conclusion

Emissions estimation models have helped the governments to evaluate the impact of their projects. However, such models require large and precise input datasets as well as calibration based on the local data. In this chapter, the impact sensitivity of the model to some of these inputs has been analyzed to prioritize the future efforts regarding the improvement and calibration of the model.

The analysis showed that the speed has a major impact on CO_2 emissions as well as temperature and ramp fraction. This result confirms the significance of the development of the local speed profiles for the purpose of the model calibration. The speed profile that is currently used in the model is the default driving cycle adapted for the condition and environment of an average American city, though it is recommended that each state develop their local driving cycle. In the case of temperature, the data is based on the average hourly temperature within a month and does not reflect the very high or low temperatures.

On the other hand, as a limiting factor to this study was that the fleet dataset did not provide reliable information on other vehicle types, such as bus and trucks. However, many studies have confirmed the significance of the emissions of the light-duty vehicles. Also, we limited the analysis to CO_2, due to the different nature of the emissions calculation of CO_2 and other GHG and pollutants. Furthermore, we did not discuss the secondary impact of the change in situation. An example of the secondary impact is that reducing congestion can encourage more people to drive, and therefore increase the total kilometers travelled, ultimately resulting in increased emissions. The other limitation of this analysis was the inevitable interaction between age and activity level, therefore, the impact of the age on emissions was left unexplained. In addition, the main challenge of the emission estimation in general, as is the case in the context of Montreal, is the availability of vehicle activity data as well as the reliability and precision of these data. However, since in this study we do not focus on the activity calculation we leave the subject open for further research and experimentation. Hence, the activity calculation as the main part of emission estimation requires careful study, evaluations and updates.

Consequently, based on the results and limitations of this analysis, the aims of future work will be to develop the local driving cycles and evaluate the impact of using the real hourly temperature distribution instead of an average monthly temperature per hour. Also, to evaluate pollutants as well as other vehicle and fuel type. Moreover, analyzing the impact of alternate strategies influencing different variables at the same time, and including the secondary impact will provide a more satisfying perspective for policy makers. In the next chapter different methods for developing driving cycles is evaluated and the most accurate method is presented.

CHAPTER 6 ENHANCING THE DRIVING CYCLE DEVELOPMENT METHODOLOGY

6.1 Methodology

As mentioned in the literature review, most of the driving cycle development methodologies follow the same structure; however they can vary with respect to some details and definitions. The general algorithm for developing the driving cycle is presented in Figure 2.16; one of the preliminary steps is defining the microtrips. The definition of microtrips is a key factor in the development of a driving cycle, since driving cycles are the collection of these smaller sections being connected together. However, the definition of microtrips is sometimes not quite clear or differs across different studies. In this section, we evaluate how different definitions can change the outputted driving cycle, in order to formulate recommendations on the most appropriate approach. To do so, we follow the same structure being used in previous studies, dividing the methodology in 5 steps.

6.1.1 Data collection

The data collection details are discussed in section 3.1.

6.1.2 Generation of microtrips

In this study we compare six different methods for defining the microtrips:

1- The sequence between two stops: a microtrip is the section of speed profile between two stops (with speed 0) that starts with an idle time followed by a driving period.

2- Fixed time intervals (three different durations): fixed time length used to define microtrips: we evaluated three time intervals: 20, 40, and 60 seconds.

3- Fixed distance (5 different distances): the data has been divided into 50, 100, 250, 500, and 1000 meters microtrips.

4- Intersections: a new microtrip starts whenever a vehicle enters a signalized intersection.
5- Fixed speed intervals: fixed ranges of speed have been identified. Each time speed passes the limits of a specific speed range a new microtrip starts. In this study, classes of speed ranges are 0,]0, 20],]20, 40],]40, 60], and]60, more], in km/h.
6- Event bins based on acceleration (3 methods): the microtrips are defined by using a clustering method on acceleration. In a first attempt two clustering approaches have been used on instantaneous acceleration: MLE (Maximum Likelihood Estimation) algorithm, and K-mean.

6.1.3 Microtrip classification

The method used for microtrips classification is the same for all the microtrips definition and is adopted from André (2004b). In this method Speed Acceleration Frequency Distribution (SAFD) is used, to define the characteristics of each microtrip, instead of the average factors, such as average acceleration, speed and stop duration. This method is selected since it can capture the fluctuations of speed and acceleration. In our study, the speed acceleration time distribution matrix of each microtrip is calculated and is compared with other microtrips and then a dissimilarity matrix is constructed. The dissimilarity matrix is the chi-square distance between two speed-acceleration distribution matrixes. Then k-means clustering method is used to classify the similar microtrips in different categories, each representing a specific driving pattern. Overall, 7 classes have been identified. Figure 6.2 and Figure 6.3 demonstrate the SAFD patterns of two of the classes: the congested and free flow conditions (for the complete figures of all the clusters, please refer to Appendix B). Figure 6.1 also shows the overall SAFD of the database.

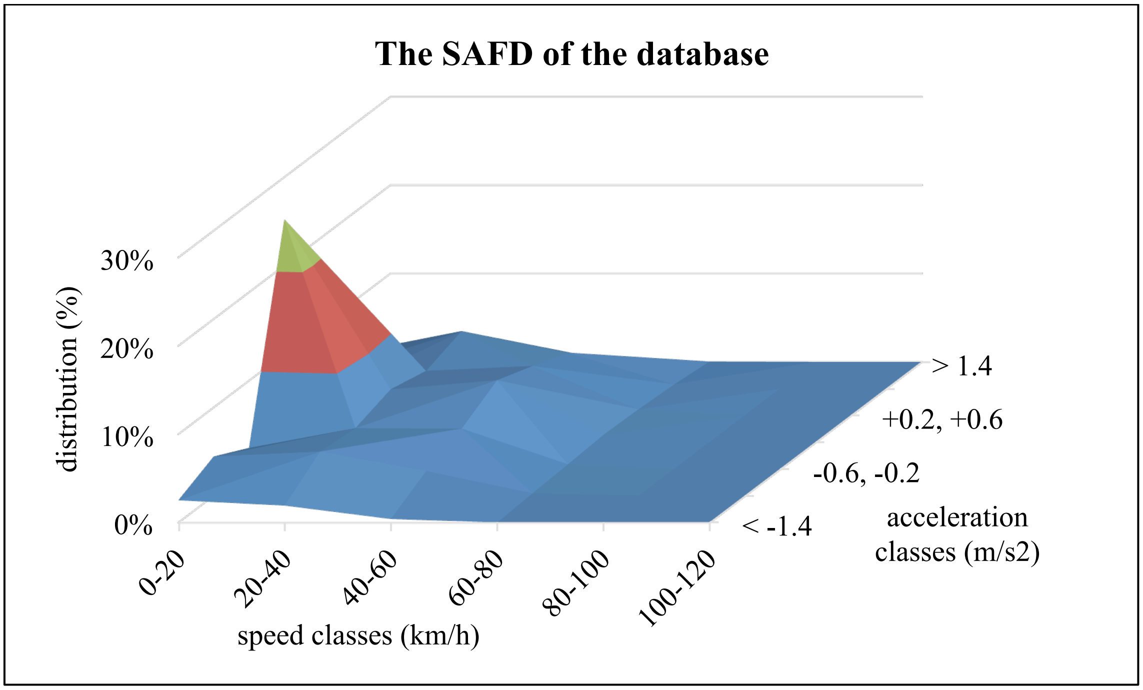

Figure 6.1: Overall speed-acceleration time frequency distribution of the database

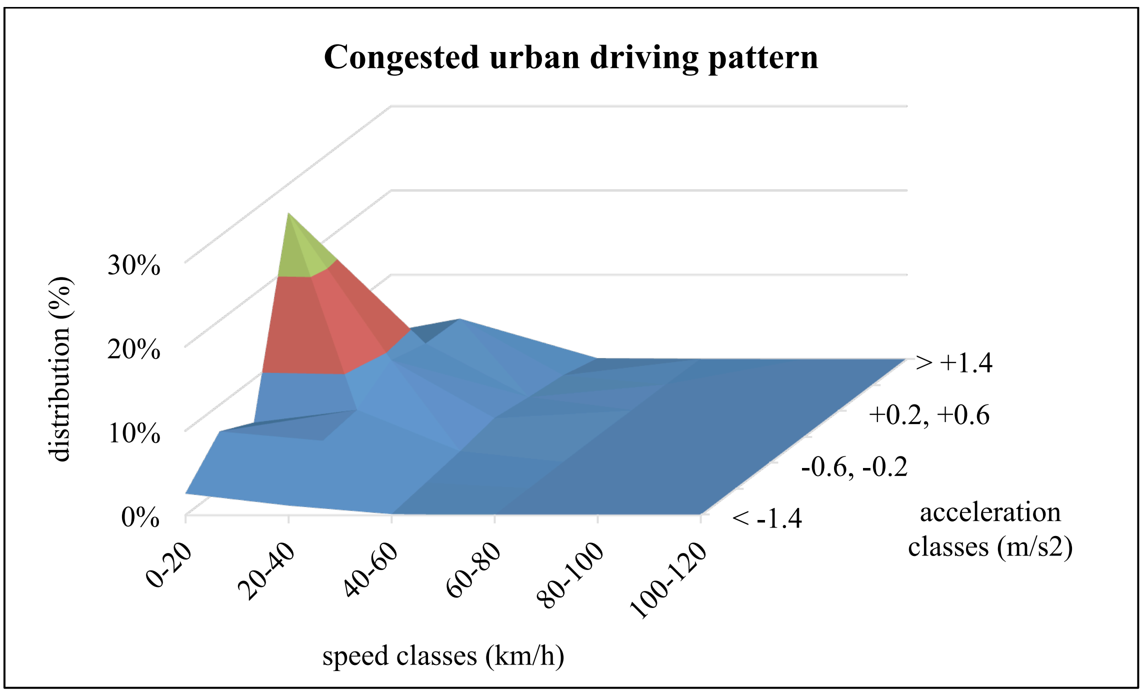

Figure 6.2: Average speed-acceleration time frequency distribution of microtrips related to congested urban driving pattern

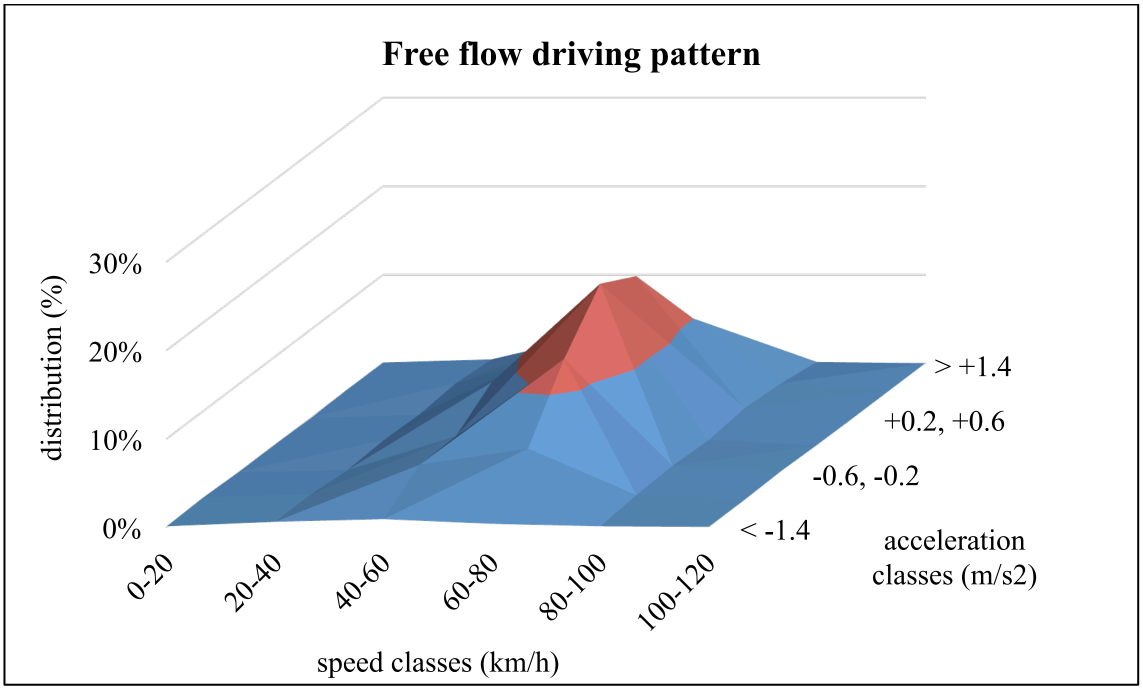

Figure 6.3: Average speed-acceleration time frequency distribution of microtrips related to high speed, free-flow driving pattern

6.1.4 Selection of assessment measures

The assessment criteria selected in this study are chosen among the most comprehensive list offered, which is found in Ashtari et al. (2014). The advantage of their list over the other studies is that they took the SAFD and road power into account. Table 6.1 shows the list of selected parameters. Each of these parameters is calculated for the entire database (observed data) and the results are set as target values.

Table 6.1: Assessment criteria

	Parameters	Unit	Values
1	Difference in SAFD	%	NA
2	Average speed of the entire driving cycle	Km/h	25.42
3	Average running speed	Km/h	31.77
4	Maximum speed	Km/h	103.84
5	Average acceleration of all acceleration phases	m/s^2	0.43
6	Average deceleration of all deceleration phases	m/s^2	-0.47
7	Average number of acceleration-deceleration changes (and vice versa) within one driving period	NA	10458
8	Root mean square acceleration	m/s^2	0.29
9	Road power	kW	5.95
	Time proportions of driving modes:		
10	Idle (speed = 0)	%	19.97
11	Acceleration (acceleration ≥ 0.1 m/s^2)	%	34.57
12	Cruising (- 0.1 m/s^2 < acceleration < 0.1 m/s^2, average speed > 5 m/s)	%	12.51
13	Deceleration (acceleration ≤ -0.1 m/s^2)	%	31.28
14	Creeping (- 0.1 m/s^2 < acceleration < 0.1 m/s^2, average speed < 5 m/s)	%	1.67

6.1.5 Construction of driving cycle

The driving cycle construction algorithm is written in R; the same code is used for all methods. R is a programming language with an open-source software interface, mainly for statistical calculations (R Development Core Team, 2015). In the first step, the starting microtrip of the driving cycle, which is being developed, is chosen within the first microtrip of each lap. There are a total number of 45 laps in the database and therefore 45 starting microtrips. It is important to note that the starting microtrips do not represent the cold start pattern since the vehicle were driven in laps and each lap does not necessarily start from idle. In this study each of the 45 starting microtrips were used to initiate the driving cycle.

In the second step, after identifying the first microtrip, the second one is selected based on the one-step marcov modeling. The marcov chain method is based on the transition matrix, which is basically the probability of different situations occurring in succession. First, the probability of one specific cluster arriving after another cluster is calculated using microtrips sequences available in our entire database. Then, for the application, a statistical probability approach is used: a first microtrip is chosen, then the following microtrip is identified based on the probabilities, and so on. After identifying the second cluster to select from, microtrips with initial speed within 2 km/h from the final second of the previous microtrip are filtered. Each microtrip from this pool is then added one by one to the first microtrip and the assessment criteria is calculated for the entire profile. A portion of the cluster sequence using transition matrix and marcov modeling is shown in Table 6.2.

Table 6.2: Cluster sequence using transition matrix and marcov modeling (CL stands for cluster) – example with 7 clusters

	End	CL_1	CL_2	CL_3	CL_4	CL_5	CL_6	CL_7
Start	0%	9%	4[illegible]%	31%	9%	0%	2%	4%
CL_1	0%	5%	35%	2%	50%	1%	7%	0%
CL_2	2%	30%	15%	51%	0%	1%	0%	2%
CL_3	0%	3%	8%	2%	76%	1%	9%	1%
CL_4	0%	22%	0%	0%	1%	57%	0%	19%
CL_5	0%	2%	1%	0%	1%	3%	91%	2%
CL_6	0%	56%	0%	0%	1%	6%	0%	37%
CL_7	0%	2%	90%	1%	6%	0%	1%	1%

The final selection is based on assessment criteria; hence, the microtrip that is closest to the target value is chosen. After choosing the best microtrip, the algorithm continues with repeating the second step and adding another microtrip. The iteration continues until the profile reaches the target duration. In this case the target duration is 46 minutes, which is the average duration of all the laps.

After developing all the 45 driving cycles for each method, to determine the best fit, a ranking method similar to the process in Ashtari et al. (2014) is used. Based on this method, first, the difference between the new profile and the target profile is calculated in an n x 14 matrix; n is the number of microtrips in the pool and 14 is the number of assessment parameters. Second, the matrix is sorted again based on the values of each parameter and the rank of each profile is recorded in another n x 14 matrix. Finally, all the ranks are added together; consequently the profile that has the lowest global ranking is the best profile.

This procedure is repeated for each microtrip definition and a total number of 14 driving cycles are produced based on 14 different definitions of microtrips. At the end, the assessment measures of the driving cycles are compared with the target values and the best definitions are identified.

6.2 Comparison of different methods

As mentioned in the methodology, six main definitions of microtrips are evaluated in this study. Each microtrip definition affects the characteristics of the microtrips as well as the driving cycle. One of the main characteristics is the length of the microtrip. Figure 6.4 demonstrates the cumulative distribution of the length of the microtrips. The figure demonstrates that the definitions can be classified in two distinct categories regarding the duration of microtrips. Certain definitions resulted in very short microtrips such as: MLE, speed intervals and k-mean. It is discussed that very short microtrips cannot represent realistic driving behaviour and in both MLE method and K-means method 80% of the microtrips are shorter than 10 seconds.

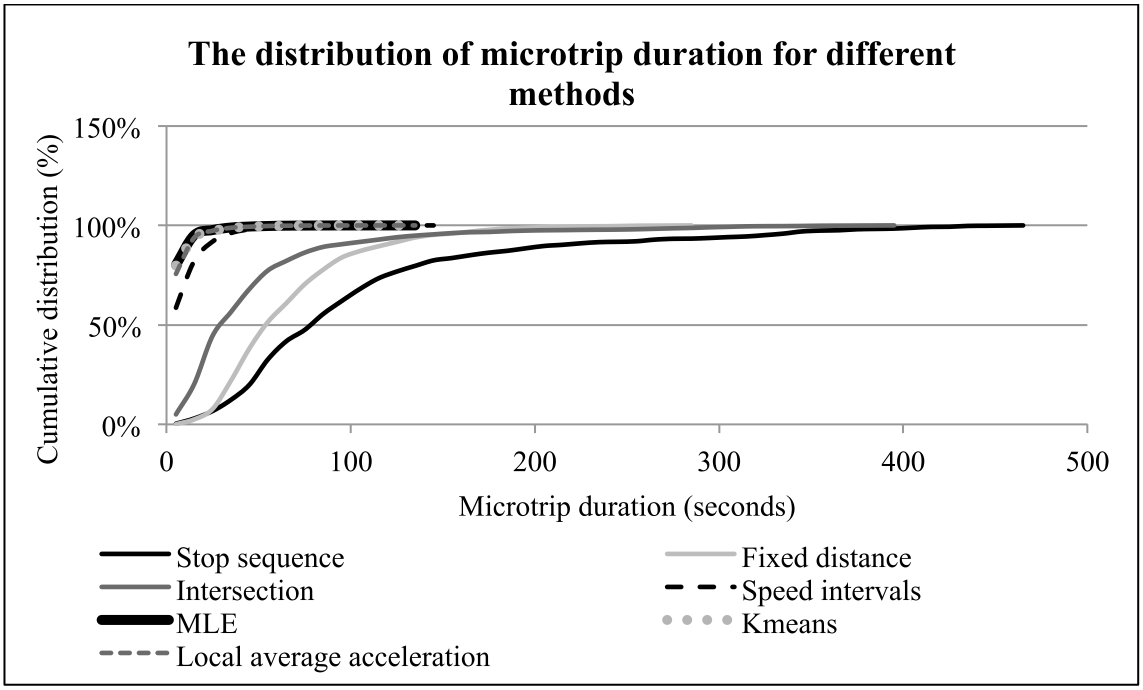

Figure 6.4: Distribution of microtrip duration for different methods used for identifying microtrips

Also, since the acceleration is calculated from speed directly, as we can see in Figure 6.5, the microtrip division shows a noise-like behaviour. Therefore, in a second attempt we tried to smooth the acceleration profile. In the smoothing technique, the moving average method was used, where we calculated the average acceleration considering each second's acceleration and 2 seconds before and after each point. This method resulted in minor improvement in noise reduction of the acceleration profile and reduced the percentage of microtrips below 10 seconds to 75%.

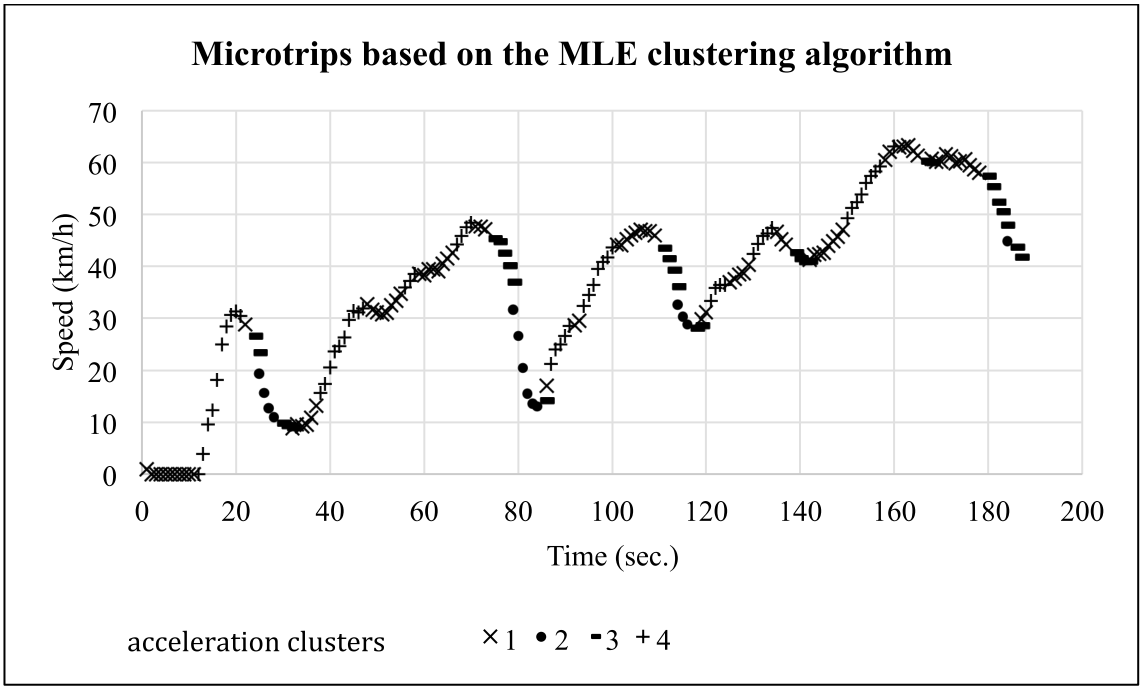

Figure 6.5 Microtrip divisions based on MLE clustering algorithm on acceleration profile

The other category of microtrips definition consists of longer microtrips which are the definitions based on stop sequence, intersection and fixed distance. The fixed-time definition is not demonstrated in this figure since all the microtrips fall in the same duration. In some literature it is mentioned that very short microtrips may not result in representative cycles (André, 2004a) whereas the other studies do not consider that fact in their analysis. For example, the MLE and K-means clustering method, which result in very short microtrips, claim that they can cover driving characteristics better than any other method, since they are based on the acceleration event (Lin & Niemeier, 2002). In this study, both methods (removing and keeping the microtrips under 10 seconds) were examined, and no significant difference was found between the two in regards to the ranking of each method.

After the construction of driving cycles, all are compared to the target values and are rated to determine the best driving cycle. A total of 8 driving cycles are developed, one for each method. To compare different methods a ranking process has been used. In the ranking process, firstly the difference between the target value of the assessment measures and the value of the assessment measures calculated for each driving cycle method is calculated.

Then, the results are sorted in ascending order for each assessment measure and a rank is given to each method. This process is repeated for each assessment measures and all the ranks are summed together to determine a total rank for each driving cycle. Based on the ranking process (using all criteria), the methods are classified as follows, in descending order of performance:

1- Fixed distance (best result for 250 m)
2- Intersection
3- Stop sequence
4- Fixed time (best result for 40 seconds)
5- Event bin based on average local acceleration
6- Fixed speed ranges
7- Event bin based on MLE
8- Event bin based on k-means

Also the differences between the average values (from the entire database) and the values using each method are provided in Table 6.3. Larger values represent larger gaps between the target values of the assessment measures and the values from the developed driving cycles.

Table 6.3: Difference between the total average values of the assessment measures of the entire database and driving cycles for each method

# Param.	250 m	Intersection	Stops	40 sec.	Ave. acc.	Speed	MLE	K-mean
1	0.2746	0.4825	0.4529	0.0853	0.2626	6.2254	12.516	0.9318
2	0.0715	0.1546	0.2002	0.2381	0.0091	0.2927	0.7595	0.5115
3	0.1436	0.2415	0.5537	0.3480	6.3350	3.6988	4.3210	6.8556
4	24.241	30.911	14.612	29.521	6.6366	7.2161	17.017	26.113
5	0.0001	0.0003	0.0025	0.0145	0.0038	0.0005	0.0016	0.0002
6	0.0010	0.0014	0.0002	0.0012	0.0213	0.0012	0.0437	0.0428
7	10136	10193	10171	10147	10179	10104	10127	10114
8	0.0075	0.0010	0.0004	0.0035	0.0000	0.0044	0.0000	0.0020
9	0.0060	0.0030	0.0059	0.0393	0.1528	0.2091	0.0425	0.0912
10	0.0014	0.0012	0.0078	0.0013	0.0042	0.0950	0.1537	0.0657
11	0.0000	0.0012	0.0051	0.0011	0.0022	0.0128	0.0350	0.0102
12	0.0009	0.0006	0.0002	0.0014	0.0004	0.0005	0.0042	0.0008
13	0.0006	0.0003	0.0021	0.0001	0.0008	0.0713	0.0505	0.0018
14	0.0002	0.0002	0.0003	0.0011	0.0025	0.0114	0.0640	0.0565

Our analysis shows that the fixed distance can provide a better definition for microtrips; to our knowledge, this method was not tested and discussed in the literature before. In addition to its performance, it is also a simple method for practitioners as it reduces the complexity of driving cycle development procedure. Also, since this method results in longer microtrips comparing to the event bin methods, the development process is much less time consuming. The time issue can also become more critical in larger databases where years of data are available (For figures of driving cycles regarding each method you can refer to appendix C).

6.3 Conclusion

The results confirmed that the definition of microtrips have a significant influence on the development of driving cycle despite the fact that it is usually undermined. In this study, it is discovered that the spatial methods for defining the microtrips are the best. In the first attempt it was discovered that the distance-based method (500 m) provides the best result between different spatial definitions. In a second attempt, more distances were evaluated: 50, 100, 250, and 1000 meters. Among all the 250 meters provided the best result. In a previous study it has been stated that the event bin method can provide the most precise method of microtrip generation, which was not confirmed in our results. This study asserts the importance of the microtrip generation method and their role in driving cycle development. With driving cycles being the backbone of the most recent emissions models, it is therefore crucial to be conscious of such details.

The driving cycle development procedure requires very extensive database including different types of car, driver, driving situation, etc. to be representative of the population. The limited resources for data collection and having to work with a relatively small database were some of the limitations of this study. It would be interesting to use a database with normal daily trip method for a longer period of time covering more vehicle types and situations. As a further study, such databases can be used to develop the necessary driving cycle to use in emissions models to evaluate the impact of different microtrip generation method on the total emissions.

CHAPTER 7 CONCLUSION

The main objective of this research was to enhance the emissions estimation process for passenger vehicles by identifying the variables having an incidence on the estimations and the level of variability of the outcomes, analysing the variability of estimations when using typical modelling tools as well as the sensitivity of driving cycle structures to the development procedure used. It aimed at evaluating the available methodologies and identifying the possible improvements, while considering the characteristics of the local activity and weather conditions. This conclusion summarizes the main findings of this study as well as contributions, limitations, and the recommendations for the future research.

7.1 Summary of the studies

As mentioned previously, the main objective of this research is to enhance the emissions estimation methods, and to do so, four specific objectives have been identified. These four objectives and the results of the synthesis are as follows:

1. The first specific objective was to review, evaluate, and clarify the process and methods of emissions estimation. Chapter 2 is dedicated to this objective. As explained, the emissions estimation is based on different elements: emissions testing, activity calculation, and the actual emissions estimation process. These three elements always go hand in hand, and the results of the analysis, in terms of scale and accuracy, depend on every one of them. In this chapter, we evaluated those elements separately and discussed different methods, their advantages and their limitations as well as the gaps in the literature.

2. The second objective, which is covered in Chapter 4, was to understand the available emissions estimation and fuel consumption models and to demonstrate the impact of different input variables on fuel consumption. In this chapter, we evaluated different emissions models (i.e. equations) for instantaneous fuel consumption estimation and selected the most comprehensive for our analysis.

Based on these equations, we explored how fuel consumption is influenced by different variables and how local characteristics can amplify or reduce the magnitude of this influence. For example, the AC has a significant impact on fuel consumption; however, there is no data available to evaluate the proportion of times when the users turn on the air conditioning. The same situation applies to the heating. There are limited studies focusing on the impact of heating on fuel consumption, which is even more important in Quebec. Available methods assume that when the temperature rises more than the comfort zone, the users turn on the air conditioning. But this assumption cannot demonstrate whether educating the drivers towards eco-driving can have any impact on their behaviour. These assumptions need to be evaluated by the researchers and practitioners, notably the fact that a large amount of research has focused on the impact of the pavement on fuel consumption while its impact is minimal comparing to the other factors. The necessity of investing more attention to the other variables as well is highlighted in this chapter. As mentioned before, these models are usually the backbone of the emissions estimation software and understanding their functions can shed light on the main structure of more complicated emissions software.

3. The next objective was therefore dedicated to understand and evaluate MOVES, one of the most comprehensive, yet complicated emissions simulators available. MOVES is the emissions model used across North America, including the province of Quebec. It is however a model initially developed in the U.S., which nonetheless reflects the general characteristics of American cities. It is even recommended in the U.S. for each state to “localize” the model. In this chapter a sensitivity analysis is conducted to understand how different variables, namely the input database, can impact the result. The activity and other emissions related databases are never perfect. Evaluating, improving, and updating the emissions models should be an ongoing process. During this chapter we defined which databases are prone to more errors in the output; therefore, these should be prioritized in the enhancement process.

4. Drivers' behaviour or their speed profile is one of the main elements for emissions estimations. Since it is not yet possible to record it for all the vehicles at all times, a representative speed profile, namely a driving cycle, is often used to demonstrate the average driving behaviour. To construct a driving cycle, the speed profiles are divided into smaller pieces, called microtrips. The definition of microtrips and their role in the performance of the driving cycles are often neglected. Chapter 6 is dedicated to evaluating different definitions of driving cycles as well as to introduce other possibilities. The analysis of different methods demonstrated that the spatial definitions result in the most representative driving cycles. It also confirmed that the methods resulting in very small microtrips do not provide the best driving cycles.

7.2 Contributions

The original contributions of this study based on the main three axes presented are as follows:

1. A comprehensive analysis of the available fuel consumption models and comparative evaluation of different factors. The factors that are demonstrated in the study are vehicle characteristics (such as weight, engine size, and aerodynamic characteristics), the speed profile, ambient condition (i.e. temperature and wind speed), and road characteristics (i.e. pavement texture and road grade). First, the comprehensive review of the previous studies highlighted the gaps and shortcomings of the emissions estimation models and offered perspectives for further research. Also, the comparative analysis provides a good understanding of the priorities for improving the available models by demonstrating the magnitude of the impact of each variable in comparison to the rest of the factors. Based on the findings, AC, engine capacity (litre), cold start, average link speed, and vehicle weight (kg) are the 5 most influencing factors on vehicle emissions respectively. The results of this analysis are mainly useful for the policy makers to have a better understanding of the emission estimation process as well as for the future studies.

The main contribution of this analysis is the novel sensitivity analysis method developed, which enables us to compare the factors that are different in nature. This method enables researchers to evaluate different factors with different characteristics. The results are helpful for ranking the impact of sets of variables based on their known threshold.

2. A sensitivity analysis of the MOVES model providing a unique analysis method considering different factors such as distribution, the geographical characteristics, and the magnitude of influence of each input database. The original contribution of this research is proposing a methodology to compare different factors with different nature and different distributions. The specific characteristic of this method in addition to previous method is consideration of distribution. In studies that distribution plays an important role in results this method can help the researchers to consider the variation of distribution as well as the impact of the factor together.

3. The most significant contribution of this research is an improvement in the driving cycle development methodology by introducing a new definition for microtrips. The studies of driving cycle usually undermine the importance of microtrip in driving cycle development in contrary to the fact that the driving cycles are made of these smaller sections. Certain studies proposed new definitions for microtrip and claiming the method can improve the driving cycle since it is based on detailed characteristics; however, in this study by comparing all ranges of methods for generating microtrips we found that both very short and very long microtrip do not result in the most representative microtrips. Also, in addition to the methodological improvement, the vehicle activity data collected for this study can contribute to the future research. Since the dataset includes high definition speed data (more than 1 recording per second) such datasets can be useful for calibrating microscale traffic model as well as macroscale transportation model.

7.3 Limitations

Along with the analysis of the three main axes of this study some limitations and challenges became evident:

1. Regarding the emissions models, some equations were inexistent or unavailable making the process of sensitivity analysis difficult. For example, the models regarding the AC or cold start excess emissions were adopted from the European models making the assumption that more recent vehicles in Europe and in the US resemble in terms of emission levels.
2. Regarding the sensitivity analysis of MOVES, limited documentation was found on the equations used for estimating the cold start emissions. Also, the documentation on MOVES is limited to the structure of the model and the details of calculations are missing. Also, the dependence of different factors made it difficult to do the analysis one step at a time.
3. Regarding the driving cycle development, the drivers who assisted in gathering the information had similar profiles (all Polytechnique students). Also the vehicle and the driving route were constant, which makes the driving cycle developed not representative or the entire Montreal area. Therefore, in our analysis we limited the results to evaluation of the different methodology.

7.4 Perspectives

The results of this study, as well as the limitations that were discussed, provide some perspectives for future research. Here are some of the potential leads for further studies:

1. Based on the findings of the first section there are still certain aspects of emission modeling that have been undermined. For example, it is confirmed in all studies that the use of AC can increase the fuel consumption significantly. However, there is no data available on the drivers' habit. More clearly, we do not know if under a certain condition a driver will use AC. There are some studies that assume that if the combination of temperature, humidity, and sun

radiation exceeds a certain limit (thermal comfort) the driver will turn on the AC. However, the drivers' and the passengers' preferences are usually not as simple. Also, vehicles with better insulation can reduce the impact of the outdoor temperature and sun radiations. Therefore, it is absolutely necessary to record and observe the use of such features inside the vehicle. In addition to AC, the vehicles' heating system is one of the subjects that requires further attention. As mentioned, the older heating systems drew the heat from the engine. But with recent advances in engine technology less heat escapes from the engine and more recent heating systems depend on the electricity that is produced from the combustion and therefore consumes extra fuel for its production. Moreover, the heating system in recent cars is not limited to the hot air blown from the air dock; nowadays, almost all parts of the cars can be heated (e.g. seats, steering wheel, windows, mirrors, etc.). The impact of heater is specifically important to capture in cold climates such as Quebec's. Furthermore, in general, all additional options can increase the fuel consumption, such as the screens, refrigerators, etc. The emission models and the consumers' behaviour is a subjects that needs regular and continuous updates and analysis. Thanks to the new technologies for recording all the information from the vehicle computer (i.e. OBDII datalogger) it is possible to record such activities. The results of such data collection can enables researchers to provide a comprehensive set of equations to calculate emissions that will be available to other researchers as well as practitioners for some cases where the emissions models are not capable or not flexible enough to faithfully calculate emissions. To summarise, a comprehensive vehicle survey is necessary to keep emission models and activity distribution up to date.

2. Emission models such as MOVES are sensitive and relatively complex which can easily result in errors. It is absolutely necessary to keep the input databases up-to-date as well as to use local values instead of defaults. Furthermore, each model has certain limitations and capabilities; researchers and practitioners

should be aware of both to be able to adapt their expectations and understand their margin of errors. For example, as explained in Chapter 5, regarding the temperature, MOVES considers an average hourly temperature throughout a month. This approach might be less problematic in climates with less temperature variability. However, in Quebec we can observe a large change in temperature in one month. Also, MOVES, fails to consider certain detail comparing to its European counterparts. For example, there is only one category of passenger vehicle available and all the values are calculated for a representative average vehicle.

3. Regarding the local driving cycles, returning to the first point, a comprehensive data collection is required to be able to develop a representative driving cycle. Such data collection is relatively low cost and can be useful for other purposes such as improvements and calibration of transportation demand models or even microscale traffic models.

BIBLIOGRAPHY

Ahn, K., Kronprasert, N., & Rakha, H. (2009). Energy and Environmental Assessment of High-Speed Roundabouts. *Transportation Research Record: Journal of the Transportation Research Board, 2123*(-1), 54-65. doi: 10.3141/2123-07

Ahn, K., & Rakha, H. (2008). The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D: Transport and Environment, 13*(3), 151-167. doi: http://dx.doi.org/10.1016/j.trd.2008.01.005

Ahn, K., Rakha, H., Trani, A., & Van Aerde, M. (2002). Estimating Vehicle Fuel Consumption and Emissions based on Instantaneous Speed and Acceleration Levels. *Journal of Transportation Engineering, 128*(2), 182-190. doi: doi:10.1061/(ASCE)0733-947X(2002)128:2(182)

Ajtay, Delia, & Weilenmann, Martin. (2004). Compensation of the exhaust gas transport dynamics for accurate instantaneous emission measurements. *Environmental science & technology, 38*(19), 5141-5148.

Akçelik, R. (1983). Progress in fuel consumption modelling for urban traffic management: Australian Road Research Board.

Akçelik, R., & Biggs, D. C. (1985). A discussion on the paper on fuel consumption modeling by Post et al. *Transportation Research, Part B (Methodological), 19B*(6), 529-533. doi: 10.1016/0191-2615(85)90048-7

Akçelik, R., Smit, R., & Besley, M. (2014). *Recalibration of a vehicle power model for fuel and emission and its effect on assessment of alternative intersection treatment*. Paper presented at the The 4th International Roundabout Conference, Seattle, WA, USA.

Al-Hasan, M. (2003). Effect of ethanol–unleaded gasoline blends on engine performance and exhaust emission. *Energy Conversion and Management, 44*(9), 1547-1561. doi: http://dx.doi.org/10.1016/S0196-8904(02)00166-8

An, F., Barth, M., Norbeck, J., & Ross, M. (1997). Development of Comprehensive Modal Emissions Model: Operating Under Hot-Stabilized Conditions. *Transportation Research Record: Journal of the Transportation Research Board, 1587*(-1), 52-62. doi: 10.3141/1587-07

Andersen, L., Larsen, J., Fraser, E., Schmidt, B., & Dyre, J. (2015). Rolling Resistance Measurement and Model Development. *Journal of Transportation Engineering, 141*(2), 04014075. doi: doi:10.1061/(ASCE)TE.1943-5436.0000673

André, M. (2004a). The ARTEMIS European driving cycles for measuring car pollutant emissions. *Science of the total Environment, 334*, 73-84.

André, M. (2004b). Real-world driving cycles for measuring cars pollutant emissions–Part A: The ARTEMIS European driving cycles. *Report Inrets-LTE, 411*, 97.

André, M., & Hammarström, U. (2000). Driving speeds in Europe for pollutant emissions estimation. *Transportation Research Part D: Transport and Environment, 5*(5), 321-335. doi: 10.1016/S1361-9209(00)00002-X

André, M., & Joumard, R. (2005). Modelling of cold start excess emissions for passenger cars: Institut National de Recherche sur les Transports et leur Securite (INRETS).

André, M., Joumard, R., John Hickman, A., & Hassel, D. (1994). Actual car use and operating conditions as emission parameters: Derived urban driving cycles. *Science of the Total Environment, 146-147*, 225-233.

André, M., Joumard, R., Vidon, R., Tassel, P., & Perret, P. (2006). Real-world European driving cycles, for measuring pollutant emissions from high- and low-powered cars. *Atmospheric Environment, 40*(31), 5944-5953. doi: http://dx.doi.org/10.1016/j.atmosenv.2005.12.057

André, M., & Rapone, M. (2009). Analysis and modelling of the pollutant emissions from European cars regarding the driving characteristics and test cycles. *Atmospheric Environment, 43*(5), 986-995. doi: http://dx.doi.org/10.1016/j.atmosenv.2008.03.013

APTA. (2009). *Recommended Practice for Quantifying Greenhouse Gas Emissions from Transit*. (APTA CC-RP-001-09).

Ardekani, S. A., & Sumitsawan, P. (2010). Effect of pavement type on fuel consumption and emissions in city driving (pp. 71): The Ready Mixed Concrete Research & Education Foundation.

Arnell, N. (2015). *Short Guide to Climate Change Risk*. Farnham, Surrey, GBR: Ashgate Publishing Ltd.

Ashtari, A., Bibeau, E., & Shahidinejad, S. (2014). Using Large Driving Record Samples and a Stochastic Approach for Real-World Driving Cycle Construction: Winnipeg Driving Cycle. *Transportation Science, 48*(2), 170-183. doi: doi:10.1287/trsc.1120.0447

Atkins, Richard D. (2009). An introduction to engine testing and development: SAE Technical Paper.

Austin, T. C., DeGenova, F. J., Caelson, T. R., Joy, R. W., & Gianolini, K. A. (1993). Characterization of driving patterns and emissions from light-duty vehicles in California.

Bai, S., Chiu, Y. C., & Niemeier, D. A. (2007). A comparative analysis of using trip-based versus link-based traffic data for regional mobile source emissions estimation. *Atmospheric Environment, 41*(35), 7512-7523. doi: 10.1016/j.atmosenv.2007.05.051

Barbusse, S., Clodic, D., & Roumégoux, J. P. (1998). Climatisation automobile, énergie et environnement. *Recherche - Transports - Sécurité, 60*(0), 3-18. doi: http://dx.doi.org/10.1016/S0761-8980(98)90036-X

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy, 38*(2), 762-769. doi: http://dx.doi.org/10.1016/j.enpol.2009.10.021

Barla, P., Miranda-Moreno, L., Savard-Duquet, N., Thériault, M., & Lee-Gosselin, M. (2010). Disaggregated Empirical Analysis of Determinants of Urban Travel Greenhouse Gas Emissions. *Transportation Research Record: Journal of the Transportation Research Board, 2156*, 160-169.

Barth, M., An, F., Younglove, T., Scora, G., Levine, C., Ross, M., & Wenzel, T. (2000). Development of a Comprehensive Modal Emissions Model *National Cooperative Highway Research Program*: Transportation Research Board.

Beckx, C., Arentze, T., Int panis, L., & Janssens, D. (2008). *Assessing vehicle emissions through an integrad activity-based modelling framework*.

Beckx, C., Arentze, T., & Janssens, D. (2007). Travel behaviour and emission assessment in the Netherlands: a different approach.

Beevers, Sean D., & Carslaw, David C. (2005). The impact of congestion charging on vehicle emissions in London. *Atmospheric Environment, 39*(1), 1-5. doi: http://dx.doi.org/10.1016/j.atmosenv.2004.10.001

Bell, K. E., Kothuri, S. M., & Figliozzi, M. A. (2013). Emission model sensitivity analysis: The value of smart phone weight-mile tax truck data.

Ben-Akiva, M.E., & Bowman, J.L. (1998). Activity Based Travel Demand Model Systems. In P. Marcotte & S. Nguyen (Eds.), *Equilibrium and Advanced Transportation Modelling* (pp. 27-46): Springer US.

Bendtsen, H. (2004). Rolling resistance, fuel consumption-a literature review.

Bester, C. J. (1984). Effect of pavement type and condition on the fuel consumption of vehicles. *Transportation Research Record*(1000), 28-32.

Bielaczyc, P., Szczotka, A., & Woodburn, J. (2011). The effect of a low ambient temperature on the cold-start emissions and fuel consumption of passenger cars. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 225*(9), 1253-1264. doi: 10.1177/0954407011406613

Biggs, D. C., & Akçelik, R. (1986). An energy-related model of instantaneous fuel consumption. *Traffic Engineering and Control, 27*(6), 320-325.

Bin, S., & Dowlatabadi, H. (2005). Consumer lifestyle approach to US energy use and the related CO_2 emissions. *Energy Policy, 33*(2), 197-208. doi: http://dx.doi.org/10.1016/S0301-4215(03)00210-6

Boere, S., Arteaga, I.L., Kuijpers, A., & Nijmeijer, H. (2014). Tyre/road interaction model for the prediction of road texture influence on rolling resistance. *International Journal of Vehicle Design, 65*(2-3), 202-221. doi: doi:10.1504/IJVD.2014.060815

Bojin, L., Ghosal, D., Chen-Nee, C., & Zhang, H. M. (2012). Reducing Greenhouse Effects via Fuel Consumption-Aware Variable Speed Limit (FC-VSL). *Vehicular Technology, IEEE Transactions on, 61*(1), 111-122. doi: 10.1109/TVT.2011.2170595

Boriboonsomsin, K., & Barth, M. (2008). Impacts of freeway high-occupancy vehicle lane configuration on vehicle emissions. *Transportation Research Part D: Transport and Environment, 13*(2), 112-125. doi: 10.1016/j.trd.2008.01.001

Boulter, P. (2009). *Emission factors 2009: Report 6-deterioration factors and other modelling assumptions for road vehicles*.

Boulter, P., Barlow, T. J., & McCrae, I. S. (2009). *Emission factors 2009: Report 3-exhaust emission factors for road vehicles in the United Kingdom*.

Boulter, P. G., Latham, S., & Ainge, M. (1999). Driving cycles for measuring passenger car emissions on roads with traffic calming measures. *Science of The Total Environment, 235*(1–3), 77-89. doi: http://dx.doi.org/10.1016/S0048-9697(99)00193-X

Boulter, P. G., McCrae, I. S., & Barlow, T. J. (2007). A review of Instantaneous Emission Models for Road Vehicles: Transportation Research Laboratory.

Boulter, P., & Latham, S. (2009). *Emission factors 2009: Report 4-a review of methodologies for modelling cold-start emissions*.

Bourget, A. (2013). Opérationnalisation du progiciel MOVES pour la modélisation des émissions de sources routières: Rapport final: AECOM.

Bowyer, D. P., Akçelik, R., & Biggs, D. C. (1985). *Guide to fuel consumption analyses for urban traffic management*.

CAA Quebec.). Effective ways to lower your fuel costs. Retrieved 28/09/2015, 2015, from https://http://www.caaquebec.com/en/on-the-road/advice/tips-and-tricks/tip-and-trick/show/sujet/effective-ways-to-lower-your-fuel-costs/

California Environmental Protection Agency. (2014). *EMFAC2014, User's Guide*.

Cappiello, A. (2002). *Modeling Traffic Flow Emissions.* (Master of Science in Transportation), Massachusetts Institute of Technology.

Cappiello, A., Chabini, I., Nam, E. K., Lue, A., & Abou Zeid, M. (2002, 2002). *A statistical model of vehicle emissions and fuel consumption.* Paper presented at the The IEEE 5th International Conference on Intelligent Transportation Systems.

Chalk, S. G., & Miller, J. F. (2006). Key challenges and recent progress in batteries, fuel cells, and hydrogen storage for clean energy systems. *Journal of Power Sources, 159*(1), 73-80. doi: http://dx.doi.org/10.1016/j.jpowsour.2006.04.058

Chaney, L., Thundiyil, K., Andersen, S., Chidambaram, S., & Abbi, Y. P. (2007). *Fuel savings and emission reductions from next-generation mobile air conditioning technology in India.* Paper presented at the VTMS 8 - Vehicle Thermal Management Systems Conference and Exhibition, May 20, 2007 - May 24, 2007, Nottingham, United kingdom.

Chen, K., & Yu, L. (2007). Microscopic Traffic-Emission Simulation and Case Study for Evaluation of Traffic Control Strategies. *Journal of Transportation Systems Engineering and Information Technology, 7*(1), 93-99. doi: http://dx.doi.org/10.1016/S1570-6672(07)60011-7

Chiu, Y. C., Bottom, J. , Mahut, M., Paz, A., Balakrishna, R., Waller, T., & Hicks, J. (2011). Dynamic Traffic Assignment *Transportation Research Circular*. Washington, DC: Transportation Research Board.

Choi, D., Beardsley, M., Brzezinski, D., Koupal, J., & Warila, J. (2011). MOVES Sensitivity Analysis:The Impacts of Temperature and Humidity on Emissions.

Clodic, D., Baker, J., Chen, J., Hirata, T., Hwang, R., Köhler, J., . . . Suwono, A. (2005). Mobile Air Conditioning *Safeguarding the Ozone Layer and the Global Climate System: Special Report of the Intergovernmental Panel on Climate Change* (pp. 295).

Cobian, R., Henderson, T., Mitra, S., Nuworsoo, C., & Suvillan, E. (2009). Vehicle Emissions and Level of Service Standards: Exploratory Analysis of the Effects of Traffic Flow on Vehicle Greenhouse Gas Emissions. *Ite Journal-Institute of Transportation Engineers, 79*(4), 30.

Coelho, M. C., Farias, T. L., & Rouphail, N. M. (2006). Effect of roundabout operations on pollutant emissions. *Transportation Research Part D: Transport and Environment, 11*(5), 333-343. doi: http://dx.doi.org/10.1016/j.trd.2006.06.005

Crowley, T. J. (2000). Causes of Climate Change Over the Past 1000 Years. *Science, 289*(5477), 270-277. doi: 10.1126/science.289.5477.270

Curry, B., & McCarthy, S. . (2011). Canada formally abandons Kyoto Protocol on climate change *Globe and Mail*. Retrieved from http://www.theglobeandmail.com/news/politics/canada-formally-abandons-kyoto-protocol-on-climate-change/article2268432/

Davis, N., Lents, J., Osses, M., Nikkila, N., & Barth, M. (2005). Part 3: Developing Countries: Development and Application of an International Vehicle Emissions Model. *Transportation Research Record: Journal of the Transportation Research Board, 1939*(-1), 155-165.

De Coensel, B., Can, A., Degraeuwe, B., De Vlieger, I., & Botteldooren, D. (2012). Effects of traffic signal coordination on noise and air pollutant emissions. *Environmental Modelling & Software, 35*(0), 74-83. doi: http://dx.doi.org/10.1016/j.envsoft.2012.02.009

De Vlieger, I. (1997). On board emission and fuel consumption measurement campaign on petrol-driven passenger cars. *Atmospheric Environment, 31*(22), 3753-3761. doi: 10.1016/S1352-2310(97)00212-4

De Vlieger, I., De Keukeleere, D., & Kretzschmar, J. G. (2000). Environmental effects of driving behaviour and congestion related to passenger cars. *Atmospheric Environment, 34*(27), 4649-4655. doi: http://dx.doi.org/10.1016/S1352-2310(00)00217-X

Delisle, F., Leblond, V., Nolet, S., & Paradis, J. (2015). *Inventaire québécois des émissions de gaz à effet de serre en 2012 et leur évolution depuis 1990*. (ISBN 978-2-550-63378-5). Ministère du Développement durable, de l'Environnement et des Parcs - Direction des politiques de la qualité de l'atmosphère.

El-Shawarby, I., Ahn, K., & Rakha, H. (2005). Comparative field evaluation of vehicle cruise speed and acceleration level impacts on hot stabilized emissions. *Transportation Research Part D: Transport and Environment, 10*(1), 13-30. doi: 10.1016/j.trd.2004.09.002

Emmelman, H. J., & Hucho, W. H. (1998). Aerodynamics of Road Vehicles.

Environment Canada. (2010). Provincial short-term trend, 2008–2009, for comparable facilities: EnvironmentCanada.

Environment Canada. (2014). *Government of Canada Takes Further Action to Reduce Greenhouse Gases (GHGs) and Air Pollution from Cars and Trucks*. Retrieved from http://news.gc.ca/web/article-en.do?mthd=index&crtr.page=1&nid=886509.

Escobar, J. C., Lora, E. S., Venturini, O. J., Yáñez, E. E., Castillo, E. F., & Almazan, O. (2009). Biofuels: Environment, technology and food security. *Renewable and*

Sustainable Energy Reviews, 13(6–7), 1275-1287. doi: http://dx.doi.org/10.1016/j.rser.2008.08.014

Esteves-Booth, A., Muneer, T., Kirby, H., Kubie, J., & Hunter, J. (2001). The measurement of vehicular driving cycle within the city of Edinburgh. *Transportation Research Part D: Transport and Environment, 6*(3), 209-220. doi: http://dx.doi.org/10.1016/S1361-9209(00)00024-9

European Comission. (2001). The costs and benefits of lowering the sulphur content of petrol & diesel to less than 10 ppm (S. D. U. a. A. a. N. Unit, Trans.): Drectorate-General Environment.

Evans, L., & Herman, R. (1976). Simplified approach to calculations of fuel consumption in urban traffic systems. *17*(8-9), 352-354.

Farzaneh, M., Schneider, W. H., & Zietsman, J. (2010). Field evaluation of carbon dioxide emissions at high speeds. *Transportation Research Record: Journal of the Transportation Research Board*(Compendex), 152-157.

Fayazbakhsh, M. A., & Bahrami, M. (2013). Comprehensive modeling of vehicle air conditioning loads using heat balance method.

Fontaras, G., & Dilara, P. (2012). The evolution of European passenger car characteristics 2000–2010 and its effects on real-world CO2 emissions and CO2 reduction policy. *Energy Policy, 49*(0), 719-730. doi: http://dx.doi.org/10.1016/j.enpol.2012.07.021

Fontaras, G., Karavalakis, G., Kousoulidou, M., Tzamkiozis, T., Ntziachristos, L., Bakeas, E., . . . Samaras, Z. (2009). Effects of biodiesel on passenger car fuel consumption, regulated and non-regulated pollutant emissions over legislated and real-world driving cycles. *Fuel, 88*(9), 1608-1617. doi: http://dx.doi.org/10.1016/j.fuel.2009.02.011

Fotouhi, A., & Montazeri-Gh, M. (2013). Tehran driving cycle development using the -means clustering method. *Scientia Iranica, 20*(2), 286-293. doi: http://dx.doi.org/10.1016/j.scient.2013.04.001

Franco, V., Fontaras, G., & Dilara, P. (2012). Towards Improved Vehicle Emissions Estimation in Europe. *Procedia - Social and Behavioral Sciences, 48*(0), 1304-1313. doi: http://dx.doi.org/10.1016/j.sbspro.2012.06.1106

Frey, H. C., Zhang, K., & Rouphail, N. M. (2008). Fuel Use and Emissions Comparisons for Alternative Routes, Time of Day, Road Grade, and Vehicles Based on In-Use Measurements. *Environmental Science & Technology, 42*(7), 2483-2489. doi: 10.1021/es702493v

Frey, H. C., Zhang, K., & Rouphail, N. M. (2010). Vehicle-Specific Emissions Modeling Based upon on-Road Measurements. *Environmental Science & Technology, 44*(9), 3594-3600. doi: 10.1021/es902835h

Gärling, T., Eek, D., Loukopoulos, P., Fujii, S., Johansson-Stenman, O., Kitamura, R., . . . Vilhelmson, B. (2002). A conceptual analysis of the impact of travel demand management on private car use. *Transport Policy, 9*(1), 59-70. doi: http://dx.doi.org/10.1016/S0967-070X(01)00035-X

Gkatzoflias, D., Ntziachristos, L., & Samaras, Z. (2007). Computer programme to calculate emissions from road transport-users manual. *European Environment Agency*.

GlobalMRV. (2015). Global MRV; Clean Air Technology. Retrieved 17-January, 2012, from http://globalmrv.com

Godefroy, F., & Morency, C. (2012). Estimating latent cycling trips in Montreal, Canada. *Transportation Research Record: Journal of the Transportation Research Board*(2314), 120-128.

Gopal, G. M., & Rajendra, S. D. (2012). Compressed Natural Gas as an Alternative Fuel for Spark Ignition Engine: A Review. *International Journal of Engineering and Innovative Technology (IJEIT), 2*(6).

Government of Canada. (2015). Historical climate data. 2015, from http://climate.weather.gc.ca/

Gyenes, L., & Mitchell, C. G. B. (1994). The effect of vehicle-road interaction on fuel consumption. In B. T. Kulakowski (Ed.), *Vehicle-Road Interaction* (Vol. 1225, pp. 225-239). W Conshohocken: American Society Testing and Materials.

Hammarström, U., Eriksson, J., Karlsson, R., & Yahya, M. R. (2012). Rolling resistance model, fuel consumption model and the traffic energy saving potential from changed road surface conditions.

Hansen, J. E., & Schmunk, R. B. (2011, 11-Aug-2011). GISS Surface Temperature Analysis. Retrieved 23-Aug, 2011, from http://data.giss.nasa.gov/gistemp/graphs/

Hao, J. Y., Hatzopoulou, M., & Miller, E. J. (2010). Integrating an activity-based travel demand model with dynamic traffic assignment and emission models: Implementation in the greater Toronto, Canada, area. *Transportation Research Record: Journal of the Transportation Research Board*(Compendex), 1-13.

Hatzopoulou, M., Miller, E. J., & Santos, B. (2007). Integrating vehicle emission modeling with activity-based travel demand modeling: case study of the Greater Toronto, Canada, Area. *Transportation Research Record: Journal of the Transportation Research Board, 2011*(1), 29-39.

Hausberger, S., Rexeis, M., Zallinger, M., & Luz, R. (2009). Emission Factors from the Model PHEM for the HBEFA Version 3.

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2012). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology*, no-no. doi: 10.1111/j.1530-9290.2012.00532.x

Helms, H., Pehnt, M., Lambrecht, U., & Liebich, A. (2010). *Electric vehicle and plug-in hybrid energy efficiency and life cycle emissions.* Paper presented at the Proceedings of the 18th International Symposium Transport and Environment, Zurich.

Holmberg, K., Andersson, P., & Erdemir, A. (2012). Global energy consumption due to friction in passenger cars. *Tribology International, 47*, 221-234. doi: http://dx.doi.org/10.1016/j.triboint.2011.11.022

Honjo, T. (2009). Thermal comfort in outdoor environment. *Global environmental research, 13*(2009), 43-47.

Hucho, W. H. (2013). *Aerodynamics of road vehicles: from fluid mechanics to vehicle engineering*: Elsevier.

Hung, W. T., Tong, H. Y., Lee, C. P., Ha, K., & Pao, L. Y. (2007). Development of a practical driving cycle construction methodology: A case study in Hong Kong. *Transportation Research Part D: Transport and Environment, 12*(2), 115-128. doi: 10.1016/j.trd.2007.01.002

Int Panis, L., Broekx, S., & Liu, R. (2006). Modelling instantaneous traffic emission and the influence of traffic speed limits. *Science of The Total Environment, 371*(1–3), 270-285. doi: 10.1016/j.scitotenv.2006.08.017

Intergovernmental Panel On Climate Change. (2007). Climate change 2007: The physical science basis *Agenda* (Vol. 6, pp. 333).

IPCC. (2007). Direct Global Warming Potentials. Retrieved 29/09/2015, 2015, from https://http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch2s2-10-2.html

IVE model. (2008). IVE Model Users Manual: Version 2.0.

Jahirul, M. I., Masjuki, H. H., Saidur, R., Kalam, M. A., Jayed, M. H., & Wazed, M. A. (2010). Comparative engine performance and emission analysis of CNG and gasoline in a retrofitted car engine. *Applied Thermal Engineering, 30*(14–15), 2219-2226. doi: http://dx.doi.org/10.1016/j.applthermaleng.2010.05.037

Jie, L., & Niemeier, D. A. (2003). Estimating Regional Air Quality Vehicle Emission Inventories:Constructing Robust Driving Cycles. *Transportation Science, 37*(3), 330-346.

Jimenez-Palacios, J. L. (1999). *Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing.* (Ph.D. 0800817), Massachusetts Institute of Technology, United States -- Massachusetts. Retrieved from http://search.proquest.com/docview/304557804?accountid=40695 ProQuest Dissertations & Theses (PQDT) database.

Johnson, V. (2002). Fuel Used for Vehicle Air Conditioning: A State-by-State Thermal Comfort-Based Approach. *SAE Technical Paper 2002-01-1957*. doi: 10.4271/2002-01-1957

Jost, P. (1992). *Emission and Fuel Consumption Modelling Based on Continuous Measurements*: TÜV Rheinland.

Joumard, R., André, M., Vidon, R., Tassel, P., & Pruvost, C. (2000). Influence of driving cycles on unit emissions from passenger cars. *Atmospheric Environment, 34*(27), 4621-4628. doi: http://dx.doi.org/10.1016/S1352-2310(00)00118-7

Joumard, R., Jost, P., Hickman, J., & Hassel, D. (1995). Hot passenger car emissions modelling as a function of instantaneous speed and acceleration. *Science of The Total Environment, 169*(1–3), 167-174. doi: 10.1016/0048-9697(95)04645-h

Kamble, S. H., Mathew, T. V., & Sharma, G. K. (2009). Development of real-world driving cycle: Case study of Pune, India. *Transportation Research Part D: Transport and Environment, 14*(2), 132-140. doi: 10.1016/j.trd.2008.11.008

Karlsson, R., Hammarström, U., Sörensen, H., & Eriksson, O. (2011). Road surface influence on rolling resistance: coastdown measurements for a car and an HGV.

Karpov, S. A. (2007). Improving the environmental and performance properties of automotive gasolines. Detergent additives. *Chemistry and Technology of Fuels and Oils, 43*(3), 173-178. doi: 10.1007/s10553-007-0030-x

Kean, A. J., Harley, R. A., & Kendall, G. R. (2003). Effects of Vehicle Speed and Engine Load on Motor Vehicle Emissions. *Environmental Science & Technology, 37*(17), 3739-3746. doi: 10.1021/es0263588

Kim, H. C., Keoleian, G. A., Grande, D. E., & Bean, J. C. (2003). Life Cycle Optimization of Automobile Replacement: Model and Application. *Environmental Science & Technology, 37*(23), 5407-5413. doi: 10.1021/es0345221

Ko, J., Park, D., Lim, H., & Hwang, I. C. (2011). Who produces the most CO_2 emissions for trips in the Seoul metropolis area? *Transportation Research Part D: Transport and Environment, 16*(5), 358-364. doi: 10.1016/j.trd.2011.02.001

Koenig, B. E., Hensher, D. A., & Puckett, S. M. (2007). Congestion and variable user charging as an effective travel demand management instrument. *Transportation Research Part A: Policy and Practice, 41*(7), 615-626. doi: http://dx.doi.org/10.1016/j.tra.2006.07.002

Koupal, J. W. (2001). Air conditioning activity effects in MOBILE6. *M6. ACE, 1*.

Koupal, J. W., DeFries, T., Palacios, C., Fincher, S., & Preusse, D. (2014). *Evaluation and Sensitivity Analysis of MOVES Input Data Submitted for the 2011 National Emissions Inventory*. Paper presented at the Transportation Research Board 93rd Annual Meeting, Washington DC.

Kuhler, M., & Karstens, D. (1978). *Improved driving cycle for testing automotive exhaust emissions*. SAE Technical Paper.

LaPointe, C. (1973). Factors affecting vehicle fuel economy. *SAE Preprints*(730791).

Lave, L., MacLean, H., Hendrickson, C., & Lankey, R. (2000). Life-Cycle Analysis of Alternative Automobile Fuel/Propulsion Technologies. *Environmental Science & Technology, 34*(17), 3598-3605. doi: 10.1021/es991322+

Lawson, D. R. (1993). "Passing the Test" – Human Behavior and California's Smog Check Program. *Air & Waste, 43*(12), 1567-1575. doi: 10.1080/1073161X.1993.10467226

Lee, C., & Miller, E. J. (2001). *A Microsimulation Model of CO_2 Emissions from Passenger Cars: Model Framework and Applications*. Paper presented at the 80th Annual Meeting of Transportation Research Board, Washington, D.C.

Lee, J. (2009). *Vehicle inertia impact on fuel consumption of conventional and hybrid electric vehicles using acceleration and coast driving strategy.* Virginia Polytechnic Institute and State University.

Leroux, M. (2005). *Global Warming - Myth or Reality?: The Erring Ways of Climatology*: Springer Berlin Heidelberg.

Leung, D. Y. C., & Williams, D. J. (2000). Modelling of Motor Vehicle Fuel Consumption and Emissions Using a Power-Based Model. *Environmental Monitoring and Assessment, 65*(1), 21-29. doi: 10.1023/A:1006498328936

Li, L., Chaosheng, H., Minghui, L., & Shuming, S. (2008, 3-5 Sept. 2008). *Study on the combined design method of transient driving cycles for passenger car in Changchun.* Paper presented at the Vehicle Power and Propulsion Conference, 2008. VPPC '08. IEEE.

Lin, J., & Niemeier, D. A. (2002). An exploratory analysis comparing a stochastic driving cycle to California's regulatory cycle. *Atmospheric Environment, 36*(38), 5759-5770. doi: http://dx.doi.org/10.1016/S1352-2310(02)00695-7

Lin, J., & Niemeier, D. A. (2003). Regional driving characteristics, regional driving cycles. *Transportation Research Part D: Transport and Environment, 8*(5), 361-381. doi: http://dx.doi.org/10.1016/S1361-9209(03)00022-1

Lincoln Navigator.). Retrieved 10/10/2015, 2015, from https://en.wikipedia.org/wiki/Lincoln_Navigator

Liu, H., Barth, M., Scora, G., Davis, N., & Lents, J. (2010). Using Portable Emission Measurement Systems for Transportation Emissions Studies. *Transportation Research Record: Journal of the Transportation Research Board, 2158*(-1), 54-60.

Lutsey, N., Brodrick, C. J., Sperling, D., & Dwyer, H. (2003). Markets for Fuel-Cell Auxiliary Power Units in Vehicles: Preliminary Assessment. *Transportation Research Record: Journal of the Transportation Research Board, 1842*, 118-126. doi: doi:10.3141/1842-14

Mandavilli, S., Rys, M. J., & Russell, E. R. (2008). Environmental impact of modern roundabouts. *International Journal of Industrial Ergonomics, 38*(2), 135-142. doi: http://dx.doi.org/10.1016/j.ergon.2006.11.003

McNally, M. G. (2008). The Four Step Model.

MERILAB. (2008). Chassis Dynamometer.

Metz, B. (2010). *Controlling climate change*. Cambridge, UK; New York: Cambridge University Press.

Metz, B. , Davidson, O.R., Bosch, P.R., Dave, R., & Meyer, L.A. (2007). Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA.

Meyer, M. D. (1999). Demand management as an element of transportation policy: using carrots and sticks to influence travel behavior. *Transportation Research Part A: Policy and Practice, 33*(7–8), 575-599. doi: http://dx.doi.org/10.1016/S0965-8564(99)00008-7

Moawad, A., & Rousseau, A. (2014). Impact of Transmission Technologies on Fuel Efficiency to Support 2017-2025 CAFE Regulations.

Montazeri-Gh, M., & Naghizadeh, M. (2007). Development of the Tehran car driving cycle. *International Journal of Environment and Pollution, 30*(1), 106-118.

Morey, J. E., Limanond, T., & Niemeier, D. A. (2001). Validity of chase car data used in developing emissions cycles. *Statistical Anaysis and Modeling of Automotive Emissions*, 15.

Murshed, D. (2010). *Estimating Greenhouse Gases from Roadway Transportation-Methodology Overview*, Kunming, China.

Nam, E. K., & Giannelli, R. (2005). Fuel Consumption Modeling of Conventional and Advanced Technology Vehicles in the Physical Emission Rate Estimator (PERE).

Natural Resource Canada. (2008). Canadian Vehicle Survey.

Natural Resource Canada. (2012, 2011-09-06). Fuel Consumption Ratings. Retrieved Feburary-22, 2012, from http://oee.nrcan.gc.ca/transportation/tools/fuel-consumption-guide/fuel-consumption-guide.cfm

Negrenti, E. (1999). The 'Corrected Average Speed' approach in ENEA's TEE model: an innovative solution for the evaluation of the energetic and environmental impacts of urban transport policies. *Science of The Total Environment, 235*(1–3), 411-413. doi: http://dx.doi.org/10.1016/S0048-9697(99)00249-1

Nesamani, K. S. (2010). Estimation of automobile emissions and control strategies in India. *Science of The Total Environment, 408*(8), 1800-1811. doi: 10.1016/j.scitotenv.2010.01.026

Ngo, D. V., Hofman, T., Steinbuch, M., Serrarens, A., & Merkx, L. (2010, 1-3 Sept. 2010). *Improvement of fuel economy in Power-Shift Automated Manual Transmission through shift strategy optimization - an experimental study.* Paper presented at the Vehicle Power and Propulsion Conference (VPPC), 2010 IEEE.

Noel, G. J., & Wayson, R. L. (2012). MOVES2010a Regional Level Sensitivity Analysis: US Department of Transportation, Federal Highway Administration.

Ntziachristos, L., & Samaras, Z. (2000). Speed-dependent representative emission factors for catalyst passenger cars and influencing parameters. *Atmospheric Environment, 34*(27), 4611-4619. doi: http://dx.doi.org/10.1016/S1352-2310(00)00180-1

Office of Energy Efficiency and Renewable Energy. (2015). 2015 idle fuel consumption for selected gasoline and diesel vehicles. Retrieved 08/10/2015, 2015, from http://energy.gov/eere/vehicles/fact-861-february-23-2015-idle-fuel-consumption-selected-gasoline-and-diesel-vehicles

Ohnishi, H. (2008). Greenhouse gas reduction strategies in the transport sector: Preliminary report *Tech. rep., OECD/ITF Joint Transport Research Centre Working Group on GHG Reduction Strategies in the Transport Sector*. Paris.

Panis, L. I. (2010). New Directions: Air pollution epidemiology can benefit from activity-based models. *Atmospheric Environment, 44*(7), 1003-1004. doi: http://dx.doi.org/10.1016/j.atmosenv.2009.10.047

Pas, E. I. (1997). *Recent advances in activity-based travel demand modeling.* Paper presented at the Activity-Based Travel Forecasting Conference.

Pearce, J. M., & Hanlon, J. T. (2007). Energy conservation from systematic tire pressure regulation. *Energy Policy, 35*(4), 2673-2677. doi: http://dx.doi.org/10.1016/j.enpol.2006.07.006

Pelkmans, L., & Debal, P. (2006). Comparison of on-road emissions with emissions measured on chassis dynamometer test cycles. *Transportation Research Part D: Transport and Environment, 11*(4), 233-241. doi: 10.1016/j.trd.2006.04.001

Plint, M. A., & Martyr, A. J. (2001). Some limitations of the chassis dynamometer in vehicle simulation. *Proceedings of the Institution of Mechanical Engineers, 215*(3), 431-431.

Post, K., Kent, J. H., Tomlin, J., & Carruthers, N. (1984). Fuel consumption and emission modelling by power demand and a comparison with other models. *Transportation Research Part A: General, 18*(3), 191-213. doi: 10.1016/0191-2607(84)90126-2

Poudenx, P. (2008). The effect of transportation policies on energy consumption and greenhouse gas emission from urban passenger transportation. *Transportation Research Part A: Policy and Practice, 42*(6), 901-909. doi: http://dx.doi.org/10.1016/j.tra.2008.01.013

Prahara, E., S. Lubis, H. A. R., & Sjafruddin, A. (1999). Development of instantaneous car fuel consumption model. *Eastern Asia Society for Transportation Studies, 3*(1), 16.

Québec in action! (2012). Retrieved 09-March, 2012, from http://www.mddep.gouv.qc.ca/changements/plan_action/index-en.htm

R Development Core Team. (2015). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org

Rakha, H., Ahn, K., Moran, K., Saerens, B., & Van den Bulck, E. (2011). *Simple Comprehensive Fuel Consumption and CO_2 Emissions Model Based on Instantaneous Vehicle Power.* Paper presented at the Transportation Research Board 90th Annual Meeting.

Recker, W. W., & Parimi, A. (1999). Development of a microscopic activity-based framework for analyzing the potential impacts of transportation control measures on vehicle emissions. *Transportation Research Part D: Transport and Environment, 4*(6), 357-378. doi: http://dx.doi.org/10.1016/S1361-9209(99)00014-0

Redsell, M., Lucas, G. G., & Ashford, N. J. (1993). Factors affecting car fuel consumption. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 207*(1), 1-22.

Richardson, A. J. (1982, May 1982). *The use of vehicle maps in the derivation of stop-start fuel consumption rates.* Paper presented at the Second Conference on Traffic, Energy and Emissions, Melbourne.

Rijkeboer, R. C., Gense, N. L. J., & Vermeulen, R. J. (2002). Options to integrate the use of mobile air-conditioning systems and auxiliary heaters into the emission type approval test and the fuel consumption test for passenger cars. http://ec.europa.eu/environment/air/transport/co2/pdf/tno_mac_fc_first_study.pdf.

Rodrigue, J. P., Comtois, C., & Slack, B. (2013). *The geography of transport systems*: Routledge.

Romm, J. (2006). The car and fuel of the future. *Energy Policy, 34*(17), 2609-2614. doi: http://dx.doi.org/10.1016/j.enpol.2005.06.025

Roorda, M. J., & Miller, E. J. (2006). Assessing transportation policy using an activity-based microsimulation model of travel demand. *ITE Journal, 76*(11), 16-21.

Roujol, S., & Joumard, R. (2009). Influence of passenger car auxiliaries on pollutant emission factors within the Artemis model. *Atmospheric Environment, 43*(5), 1008-1014. doi: http://dx.doi.org/10.1016/j.atmosenv.2008.01.016

Row, J., & Doukas, A. (2008). Fuel quality in Canada: Impact on tailpipe emissions (Prepared for the Association of International Automobile Manufacturers of Canada). In R. Franchuk (Ed.), (pp. 57). Drayton Valley, Alberta: The Pembina Institute.

Saboohi, Y., & Farzaneh, H. (2009). Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy, 86*(10), 1925-1932. doi: 10.1016/j.apenergy.2008.12.017

Saltelli, A., Chan, K., & Scott, E. M. (2000). *Sensitivity analysis* (Vol. 134): Wiley New York.

Samaras, C., & Meisterling, K. (2008). Life Cycle Assessment of Greenhouse Gas Emissions from Plug-in Hybrid Vehicles: Implications for Policy. *Environmental Science & Technology, 42*(9), 3170-3176. doi: 10.1021/es702178s

Samaras, Z., Zachariadis, T., Joumard, R., Vernet, I., Hassel, D., Weber, F. J., & Rijkeboer, R. (1998). Alternative short tests for inspection and maintenance of in-use cars with respect to their emissions performance. *International Journal of Vehicle Design, 20*(1), 292-303.

Samenow, J. (2015, July 20). Chart-topping June extends Earth's warmest period on record, *The Washington Post*. Retrieved from http://www.washingtonpost.com/blogs/capital-weather-gang/wp/2015/07/17/earths-warmest-june-keeps-2015-on-record-breaking-pace/

Schifter, I., Díaz, L., Rodríguez, R., & López-Salinas, E. (2005). A Driving Cycle for Vehicle Emissions Estimation in the Metropolitan Area of Mexico City. *Environmental Technology, 26*(2), 145-154. doi: 10.1080/09593332608618578

Schipper, L., Cordeiro, M., & Ng, W. (2007). *Measuring the carbon dioxide impacts of urban transport projects in developing countries.* Paper presented at the Proceedings of the Transportation Research Board Conference. Washington, DC. USA.

Shi, Q., Zheng, Y., Wang, R., & Li, Y. (2011). The study of a new method of driving cycles construction. *Procedia Engineering, 16*(0), 79-87. doi: http://dx.doi.org/10.1016/j.proeng.2011.08.1055

Shiftan, Y. (2000). The Advantage of Activity-based Modelling for Air-quality Purposes: Theory vs Practice and Future Needs. *Innovation: The European Journal of Social Science Research, 13*(1), 95-110. doi: 10.1080/135116100111685

Sjodin, A., Persson, K., Andreasson, K., Arlander, B., & Galle, B. (1998). On-road emission factors derived from measurements in a traffic tunnel. *International Journal of Vehicle Design, 20*(1), 147-158.

Smit, R., Ntziachristos, L., & Boulter, P. (2010). Validation of road vehicle and traffic emission models – A review and meta-analysis. *Atmospheric Environment, 44*(25), 2943-2953. doi: http://dx.doi.org/10.1016/j.atmosenv.2010.05.022

Smit, R., Smokers, R., & Rabé, E. (2007). A new modelling approach for road traffic emissions: VERSIT+. *Transportation Research Part D: Transport and Environment, 12*(6), 414-422. doi: http://dx.doi.org/10.1016/j.trd.2007.05.001

Song, G., & Yu, L. (2009). Estimation of Fuel Efficiency of Road Traffic by Characterization of Vehicle-Specific Power and Speed Based on Floating Car Data. *Transportation Research Record: Journal of the Transportation Research Board, 2139*(-1), 11-20. doi: 10.3141/2139-02

Sovran, G. (2012). *Aerodynamic drag mechanisms of bluff bodies and road vehicles*: Springer Science & Business Media.

Sovran, G., & Bonn, M. S. (1981). Formulae for the tractive-energy requirements of vehicles driving the EPA schedules.

Sperling, D., & Cannon, J. S. (2007). Chapter 1 - Introduction and Overview. In D. Sperling & J. S. Cannon (Eds.), *Driving Climate Change* (pp. 1-7). Burlington: Academic Press.

Statistics Canada. (2014). Report on Energy Supply and Demand in Canada, 1990–2012. Ottawa.

Sullivan, J. L., Baker, R. E., Boyer, B. A., Hammerle, R. H., Kenney, T. E., Muniz, L., & Wallington, T. J. (2004). CO_2 Emission Benefit of Diesel (versus Gasoline) Powered Vehicles. *Environmental Science & Technology, 38*(12), 3217-3223. doi: 10.1021/es034928d

Tamsanya, S., Chungpaibulpattana, S., & Atthajariyakul, S. (2006). *Development of automobile Bangkok driving cycle for emissions and fuel consumption assessment.* Paper presented at the Proceedings of the 2nd Joint International Conference on “Sustainable Energy and Environment (SEE 2006).

Taylor, G. W., & Patten, J. D. (2006). Effects of Pavement Structure on Vehicle Fuel Consumption - Phase III (N. R. C. o. Canada, Trans.) (pp. 98): Transportation Association of Canada.

Teisceira-Lessard, P. (2011). Quebec goes it alone with cap-and-trade climate plan, *The globe and mail*. Retrieved from http://www.theglobeandmail.com/news/politics/quebec-goes-it-alone-with-cap-and-trade-climate-plan/article4181212/

Thompson, J. K., Marks, A., & Rhode, D. (2002). Inertia simulation in brake dynamometer testing.

Tong, H. Y., Hung, W. T., & Cheung, C. S. (1999). Development of a driving cycle for Hong Kong. *Atmospheric Environment, 33*(15), 2323-2335. doi: http://dx.doi.org/10.1016/S1352-2310(99)00074-6

Tung, S. C., & McMillan, M. L. (2004). Automotive tribology overview of current advances and challenges for the future. *Tribology International, 37*(7), 517-536. doi: http://dx.doi.org/10.1016/j.triboint.2004.01.013

Unal, A., Rouphail, N. M., & Frey, H. C. (2003). Effect of Arterial Signalization and Level of Service on Measured Vehicle Emissions. *Transportation Research Record: Journal of the Transportation Research Board, 1842*(-1), 47-56.

United Nations. (2015). Kyoto Protocol. Retrieved 28/06/2015, 2015, from http://unfccc.int/kyoto_protocol/items/2830.php

USEPA. (2006). Alternative Fuels: E85 and Flex Fuel Vehicles. Ann Arbor, MI: U.S. Environmental Protection Agency.

USEPA. (2012). Motor Vehicle Emission Simulator (MOVES); User Guide for MOVES2010b (A. a. S. D. Office of Transportation and Air Quality, Trans.): U.S. Environmental Protection Agency.

USEPA. (2014). Motor Vehicle Emission Simulator (MOVES); User Guide for MOVES2014 (A. a. S. D. Office of Transportation and Air Quality, Trans.): U.S. Environmental Protection Agency.

USEPA. (2015). *Dynamometer Drive Schedules*. Dynamometer Drive Schedules. Retrieved from: http://www3.epa.gov/nvfel/testing/dynamometer.htm

Vallamsundar, S., & Lin, J. L. (2011). *MOVES versus MOBILE, a Comparison of GHG and Criteria pollutant emissions*. Paper presented at the 90th Annual Meeting of Transportation Research Board, Washington D.C.

Vallamsundar, S., & Lin, J. L. (2013). *Sensitivity Test Analysis of MOVES and AERMOD Models.* Paper presented at the Transportation Research Board 92nd Annual Meeting.

Van Wee, B., Moll, H. C., & Dirks, J. (2000). Environmental impact of scrapping old cars. *Transportation Research Part D: Transport and Environment, 5*(2), 137-143. doi: 10.1016/s1361-9209(99)00030-9

Vandenbergh, M. P., Barkenbus, J. N., & Gilligan, J. M. (2008). Individual carbon emissions: The low-hanging fruit. *UCLA Law Review, 55*, 08-36.

Vandenbergh, M. P., & Steinemann, A. C. (2007). Carbon-Neutral Individual, The. *NYUL Rev., 82*, 1673.

Várhelyi, A. (2002). The effects of small roundabouts on emissions and fuel consumption: a case study. *Transportation Research Part D: Transport and Environment, 7*(1), 65-71. doi: http://dx.doi.org/10.1016/S1361-9209(01)00011-6

Vehicle Coefficient of Drag List. (2015). Retrieved 08/10/2015, 2015, from http://ecomodder.com/wiki/index.php/Main_Page

Velupillai, S., & Guvenc, L. (2007). Tire Pressure Monitoring [Applications of Control]. *Control Systems, IEEE, 27*(6), 22-25. doi: 10.1109/MCS.2007.909477

Ville de Montréal. (2011). Nombre de véhicules en circulation. Retrieved 03-06-2014, 2014, from http://ville.montreal.qc.ca/portal/page?_pageid=6897,67889677&_dad=portal&_schema=PORTAL

Wang, G., Bai, S., & Ogden, J. M. (2009). Identifying contributions of on-road motor vehicles to urban air pollution using travel demand model data. *Transportation*

Research Part D: Transport and Environment, 14(3), 168-179. doi: 10.1016/j.trd.2008.11.011

Wang, H., Fu, L., Zhou, Y., & Li, H. (2008). Modelling of the fuel consumption for passenger cars regarding driving characteristics. *Transportation Research Part D: Transport and Environment, 13*(7), 479-482. doi: http://dx.doi.org/10.1016/j.trd.2008.09.002

Wang, T., Lee, I., Kendall, A., Harvey, J., Lee, E. B., & Kim, C. (2012). Life cycle energy consumption and GHG emission from pavement rehabilitation with different rolling resistance. *Journal of Cleaner Production, 33*, 86-96. doi: http://dx.doi.org/10.1016/j.jclepro.2012.05.001

Washburn, S., Seet, J., & Mannering, F. (2001). Statistical modeling of vehicle emissions from inspection/maintenance testing data: an exploratory analysis. *Transportation Research Part D: Transport and Environment, 6*(1), 21-36. doi: 10.1016/s1361-9209(00)00011-0

Watson, H. C., Milkins, E. E., Holyoake, P. A., Khatib, E. T., & Kumar, S. (1985). Modelling emissions from cars. *Publication of: Australian Road Research Board*.

Watson, H. C., Milkins, E. E., & Marshall, G. A. (1979). *A simplified method for quantifying fuel consumption of vehicles in urban traffic.* Paper presented at the Automotive Engineering Conference, 4th, 1979, Melbourne, Australia.

Watson, H. C., Milkins, E. E., Preston, M. O., Chittleborough, C., & Alimoradian, B. (1983). Predicting fuel consumption and emissions-transferring chassis dynamometer results to real driving conditions: SAE Technical Paper.

Watson, R. T., Meira Filho, L. G., Sanhueza, E., & Janetos, A. (1992). Greenhouse gases: sources and sinks. *Climate change*, 25-46.

Weilenmann, M. F., Alvarez, R., & Keller, M. (2010). Fuel Consumption and CO_2 Pollutant Emissions of Mobile Air Conditioning at Fleet Level - New Data and

Model Comparison. *Environmental Science & Technology, 44*(13), 5277-5282. doi: 10.1021/es903654t

Weilenmann, M. F., Vasic, A. M., Stettler, P., & Novak, P. (2005). Influence of Mobile Air-Conditioning on Vehicle Emissions and Fuel Consumption: A Model Approach for Modern Gasoline Cars Used in Europe. *Environmental Science & Technology, 39*(24), 9601-9610. doi: 10.1021/es050190j

Weilenmann, M., Favez, J. Y., & Alvarez, R. (2009). Cold-start emissions of modern passenger cars at different low ambient temperatures and their evolution over vehicle legislation categories. *Atmospheric Environment, 43*(15), 2419-2429. doi: 10.1016/j.atmosenv.2009.02.005

Welstand, J. S., Haskew, H. H., Gunst, R. F., & Bevilacqua, O. M. (2003). Evaluation of the effects of air conditioning operation and associated environmental conditions on vehicle emissions and fuel economy. *SAE transactions, 112*(4), 1993-2006.

White, C. M., Steeper, R. R., & Lutz, A. E. (2006). The hydrogen-fueled internal combustion engine: a technical review. *International Journal of Hydrogen Energy, 31*(10), 1292-1305. doi: http://dx.doi.org/10.1016/j.ijhydene.2005.12.001

Xiao, Z., Dui-Jia, Z., & Jun-Min, S. (2012). A Synthesis of Methodologies and Practices for Developing Driving Cycles. *Energy Procedia, 16, Part C*(0), 1868-1873. doi: http://dx.doi.org/10.1016/j.egypro.2012.01.286

Younglove, T., Scora, G., & Barth, M. (2005). *Designing on-road vehicle test programs for the development of effective vehicle emission models*.

Zachariadis, T., Ntziachristos, L., & Samaras, Z. (2001). The effect of age and technological change on motor vehicle emissions. *Transportation Research Part D: Transport and Environment, 6*(3), 221-227. doi: 10.1016/s1361-9209(00)00025-0

Zhang, Y., Chen, X., Zhang, X., Song, G., Hao, Y., & Yu, L. (2009). Assessing Effect of Traffic Signal Control Strategies on Vehicle Emissions. *Journal of Transportation*

Systems Engineering and Information Technology, 9(1), 150-155. doi: http://dx.doi.org/10.1016/S1570-6672(08)60050-1

APPENDICES

APPENDIX A - LOOK UP TABLES

Table A.1: The mean value CO_2 emissions (g/s) for VSP modes for vehicles with engine displacement <3.5 L (Coelho et al., 2006)

VSP	CO_2 emissions (g/s)
VSP<-2	1.6711
-2≤VSP<0	1.4580
0≤VSP<1	1.11354
1≤VSP<4	2.2333
4≤VSP<7	2.9199
7≤VSP<10	3.5253
10≤VSP<13	4.1075
13≤VSP<16	4.6350
16≤VSP<19	5.1607
19≤VSP<23	5.6325
23≤VSP<28	6.5325
28≤VSP<33	7.5852
33≤VSP<39	9.0242
39≤VSP	10.0884

Table A.2: The correction coefficient f (T, V) to calculate the cold-start excess emissions for gasoline vehicle

Vehicle technology	F (T,V)
Euro 0 without catalyst	2.602-0.079*T-0.001*v
Euro 0 with catalyst	1.048-0.002*v
Euro 1	2.654-0.089*T+0.006*v
Euro 2	1.454-0.026*T+0.004v
Euro 3	1.496-0.043*T+0.018*v
Euro 4	2.597-0.08*T

Table A.3: Coefficient a in the equation of the dimensionless excess emissions as a function of the dimensionless distance

Vehicle technology	a
Euro 0 without catalyst	-5.579
Euro 0 with catalyst	-3.050
Euro 1	-4.533
Euro 2	-9.007
Euro 3	-7.280
Euro 4	-5.544

Table A.4: The cold distance calculation for CO_2 emissions estimation

Vehicle technology	dc (T,v)
Euro 0 without catalyst	2.807-0.024*T+0.141*v
Euro 0 with catalyst	2.172+0.126*v
Euro 1	3.838+0.081*v
Euro 2	4.048-0.124*T+0.145*v
Euro 3	2.461-0.057*T+0.173*v
Euro 4	5.398-0.142*T

Table A.5: The impact of parking time on CO_2 emissions

Parking time (minutes)	g(t)
20	$0.1349*t-2.915*10^{-4}*t$
$21 \leq t \leq 720$	0.136+0.12*t
$T \geq 720$	1

APPENDIX B - THE SAFD DISTRIBUTION OF DIFFERENT CLUSTERS

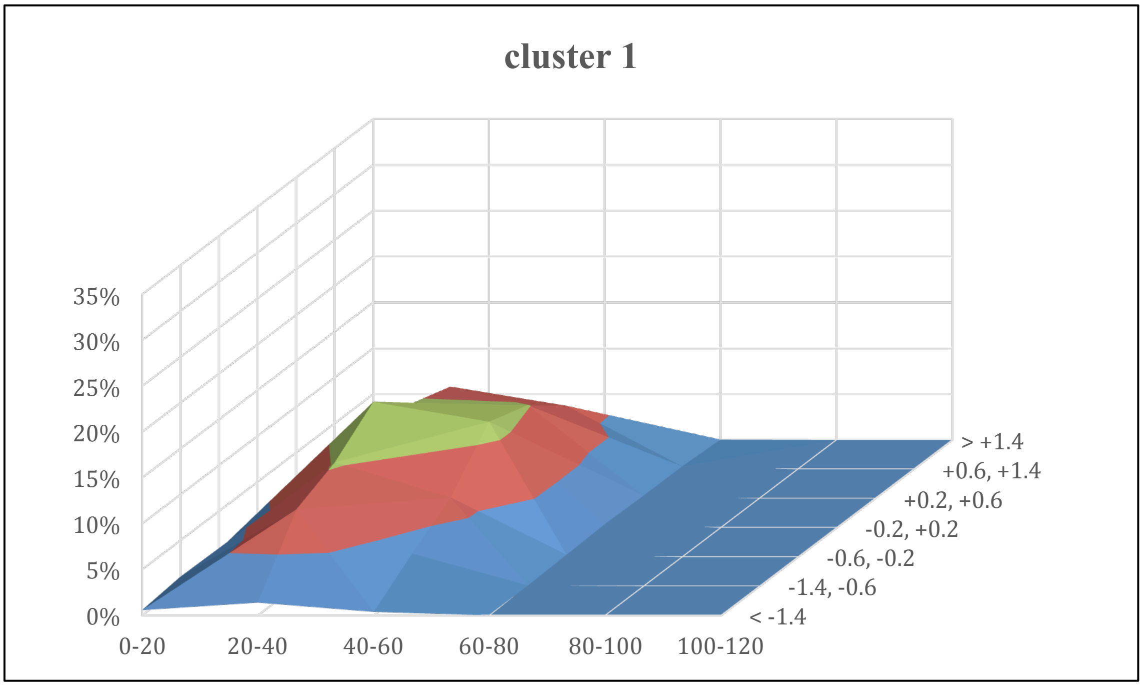

Figure B.1: The average SAFD distribution of microtrips in cluster 1

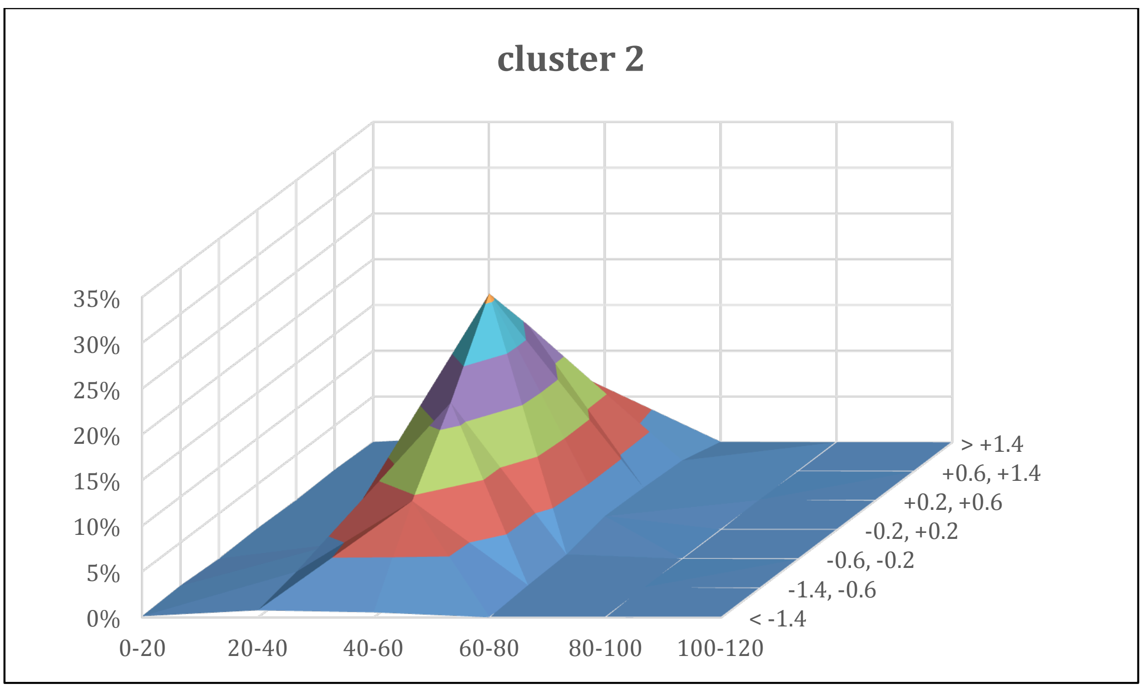

Figure B.2: The average SAFD distribution of microtrips in cluster 2

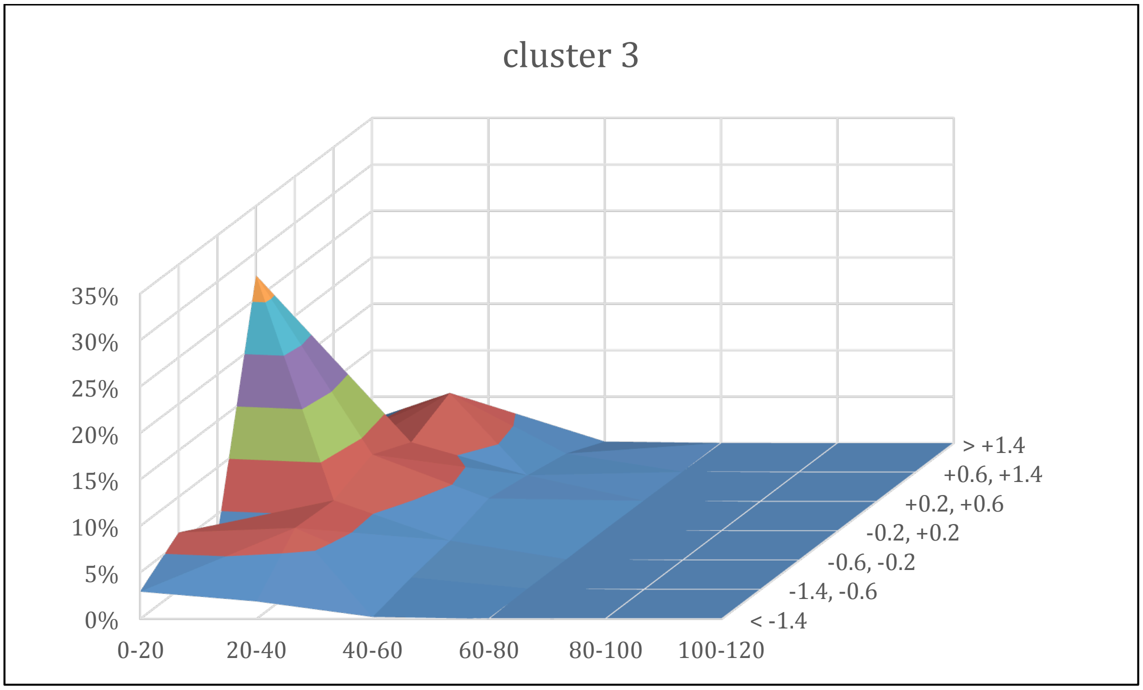

Figure B.3: The average SAFD distribution of microtrips in cluster 3

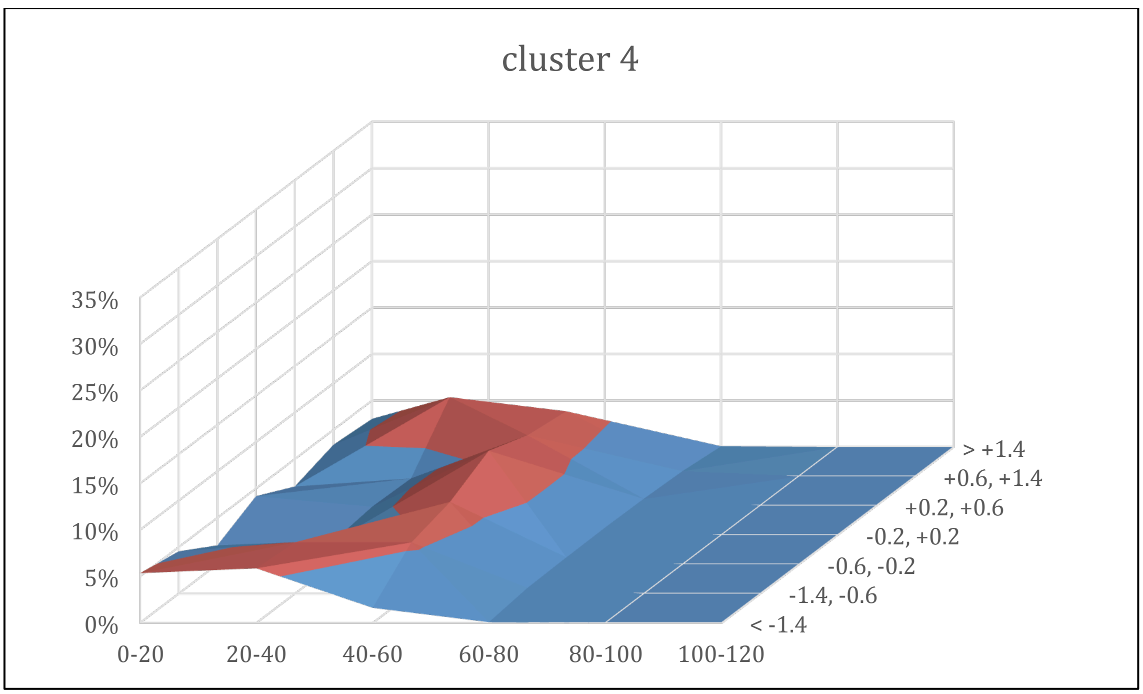

Figure B.4: The average SAFD distribution of microtrips in cluster 4

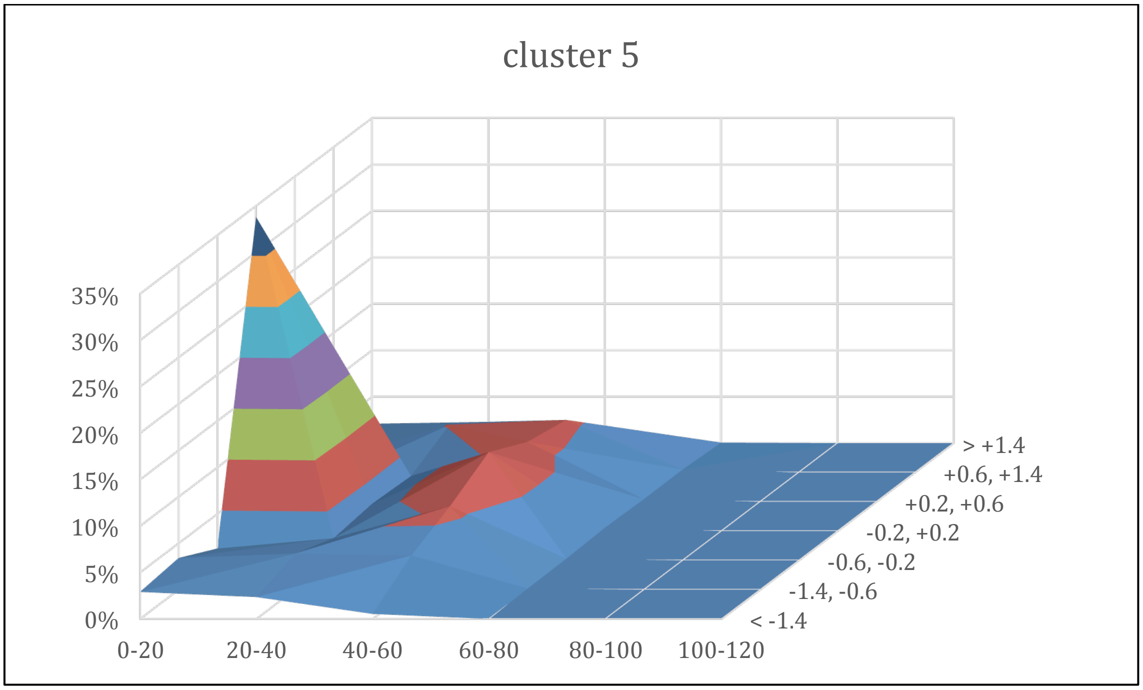

Figure B.5: The average SAFD distribution of microtrips in cluster 5

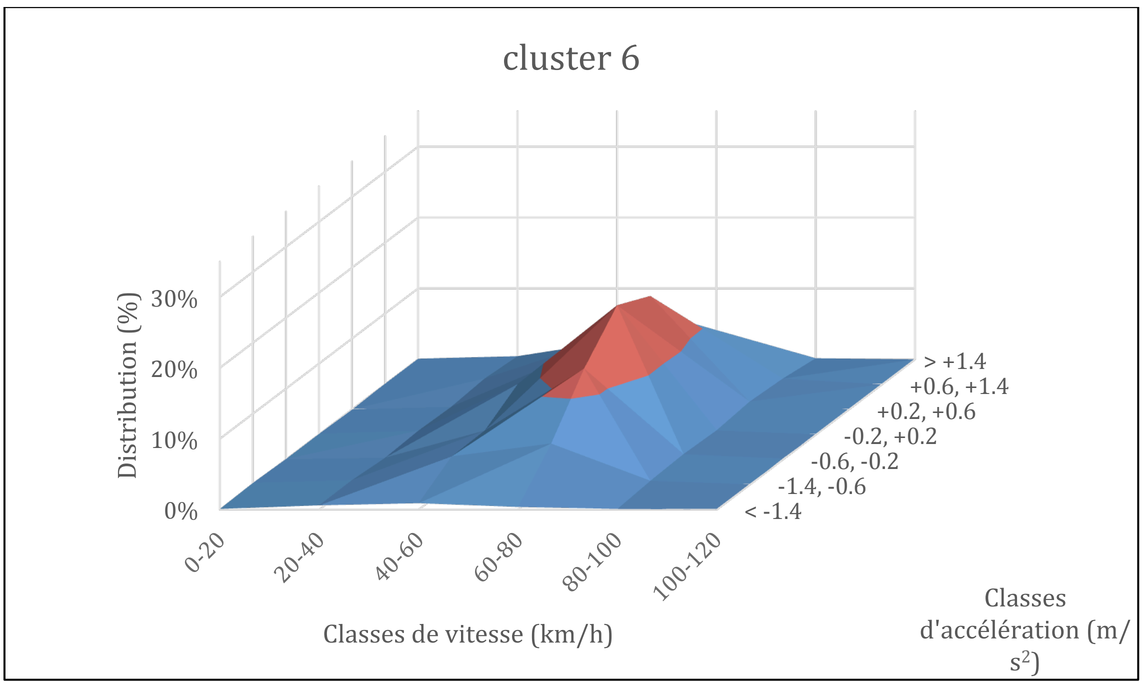

Figure B.6: The average SAFD distribution of microtrips in cluster 6

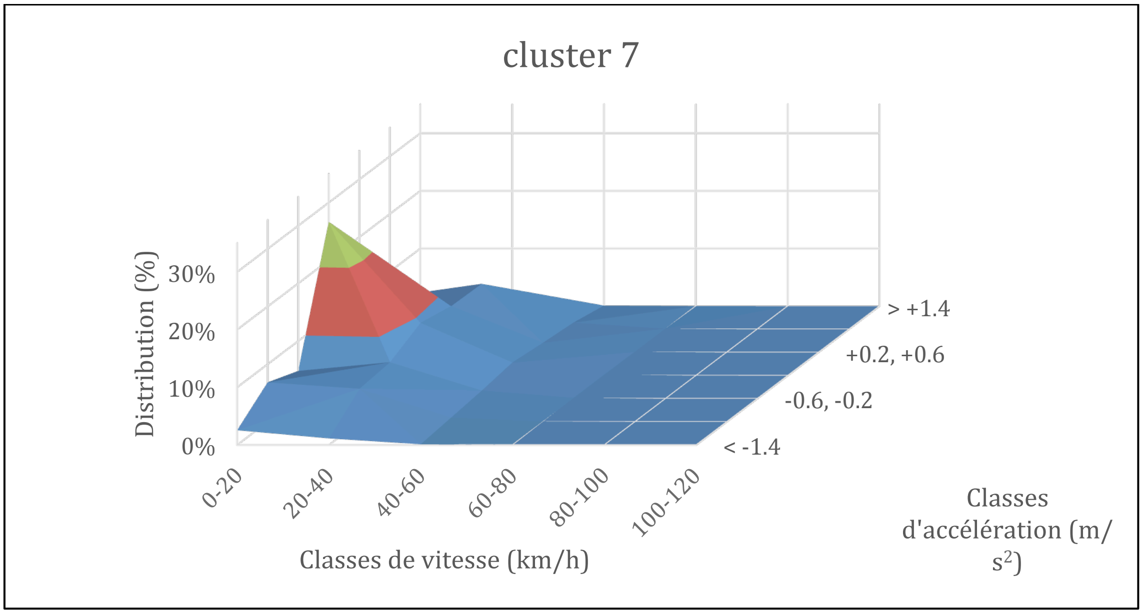

Figure B.7: The average SAFD distribution of microtrips in cluster 7

APPENDIX C - THE DRIVING CYCLE DEVELOPED BY DIFFERENT MICROTRIP METHODS

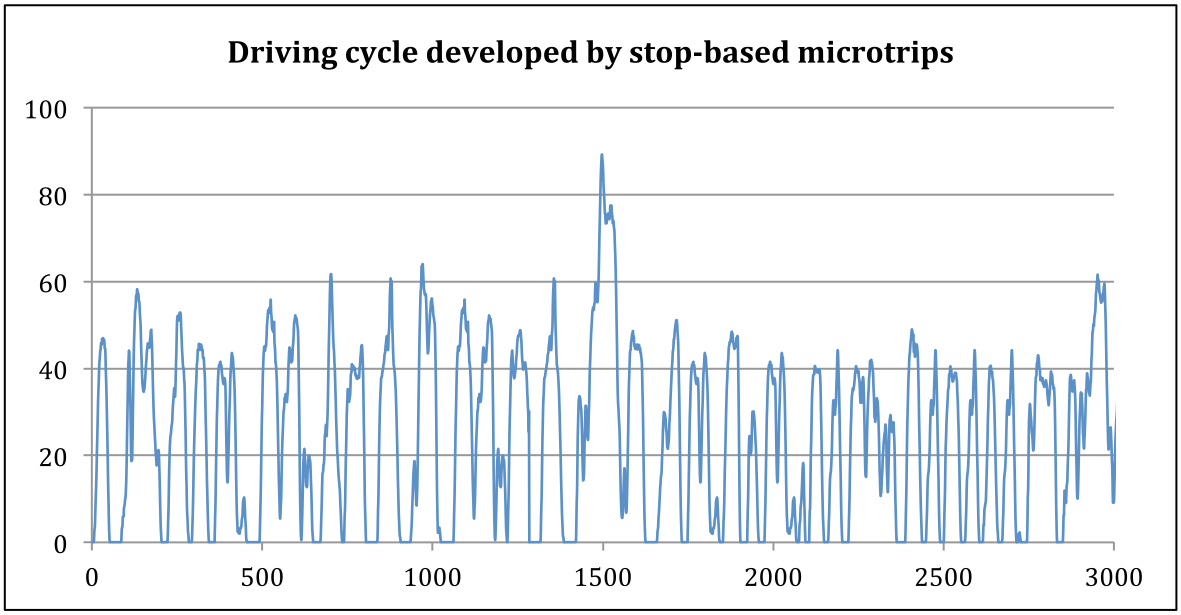

Figure C.8: The driving cycle developed based on the stop sequence microtrip

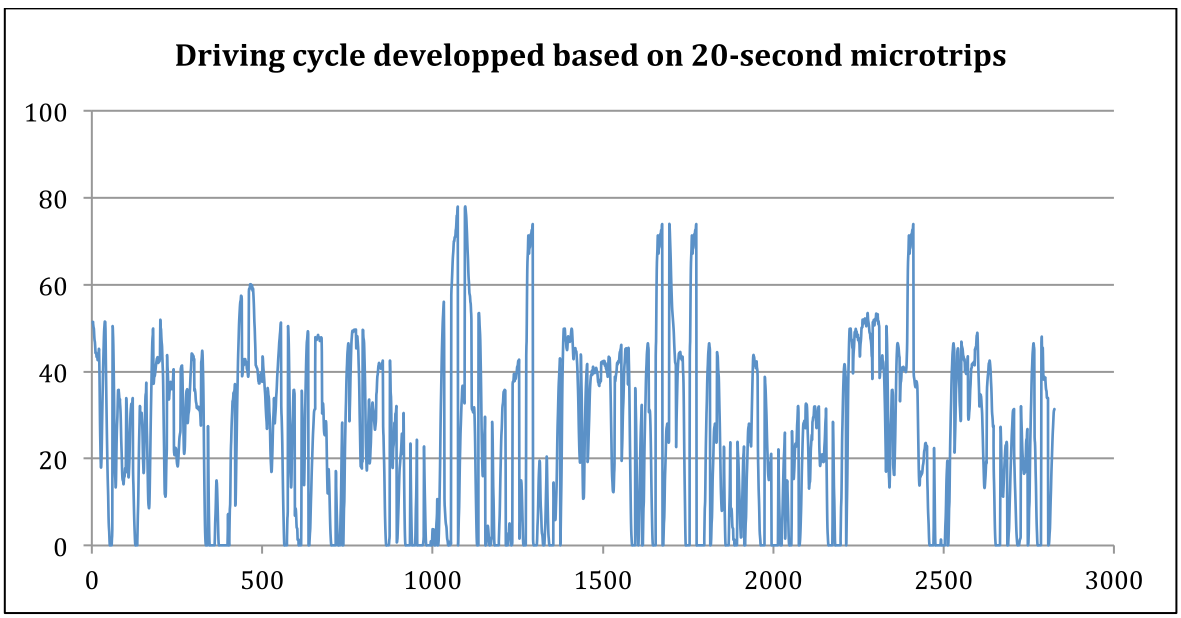

Figure C.9: Driving cycle based on the 20-seconds microtrips

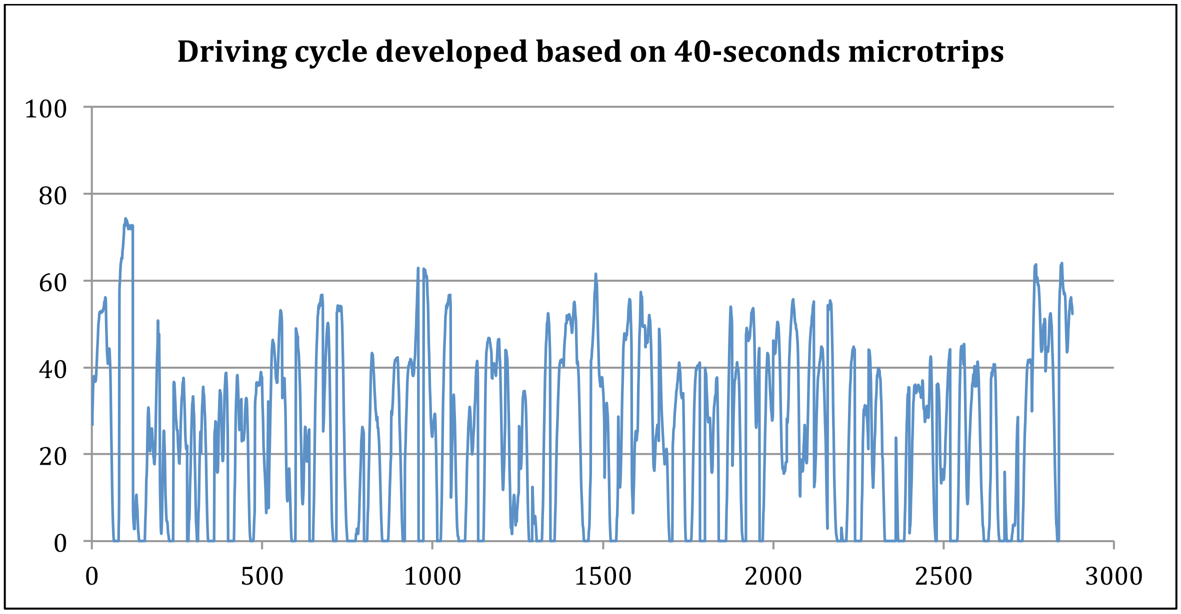

Figure C.10: The developed driving cycle based on 40-seconds microtrips

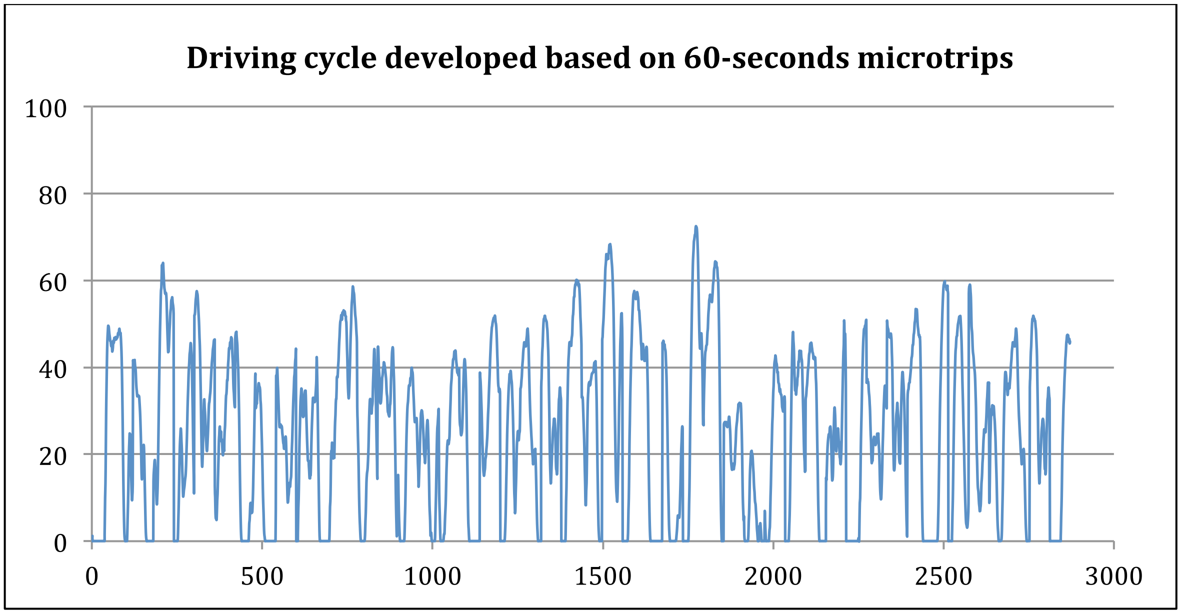

Figure C.11: The developed driving cycle based on 60-seconds microtrips

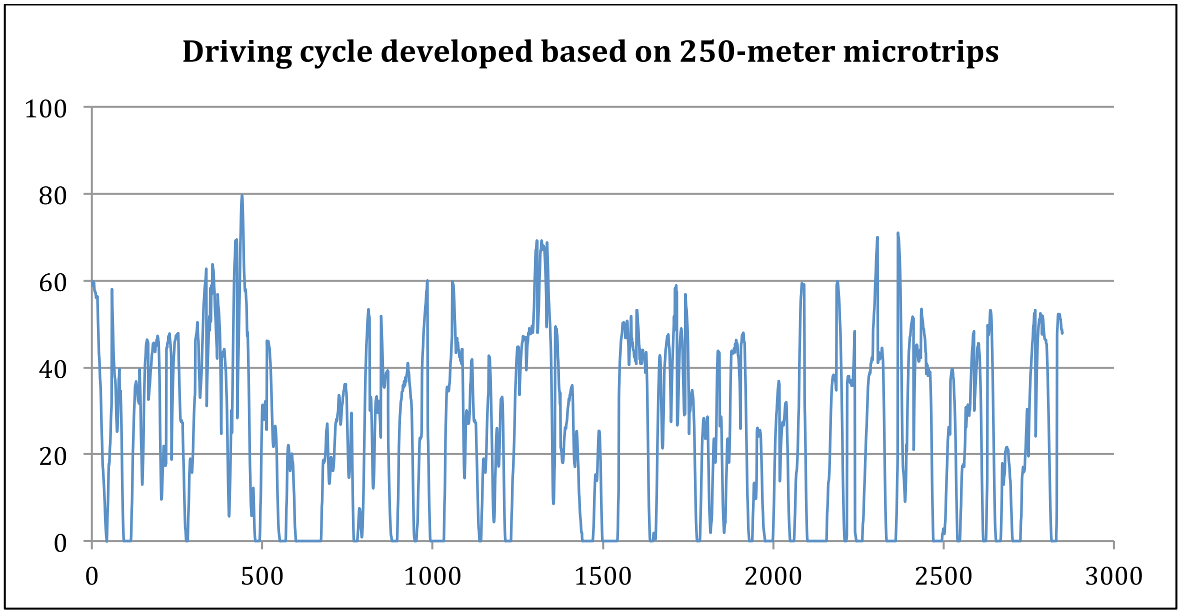

Figure C.12: The developed driving cycle based on 250-meter microtrips

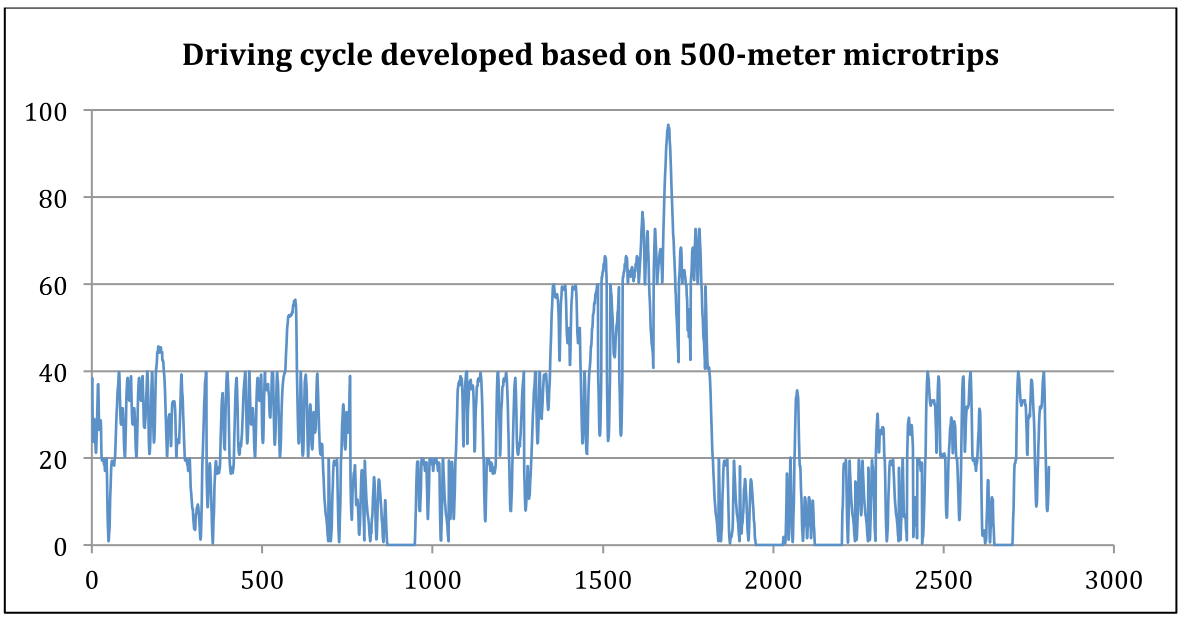

Figure C.13: The developed driving cycle based on 500-meter microtrips

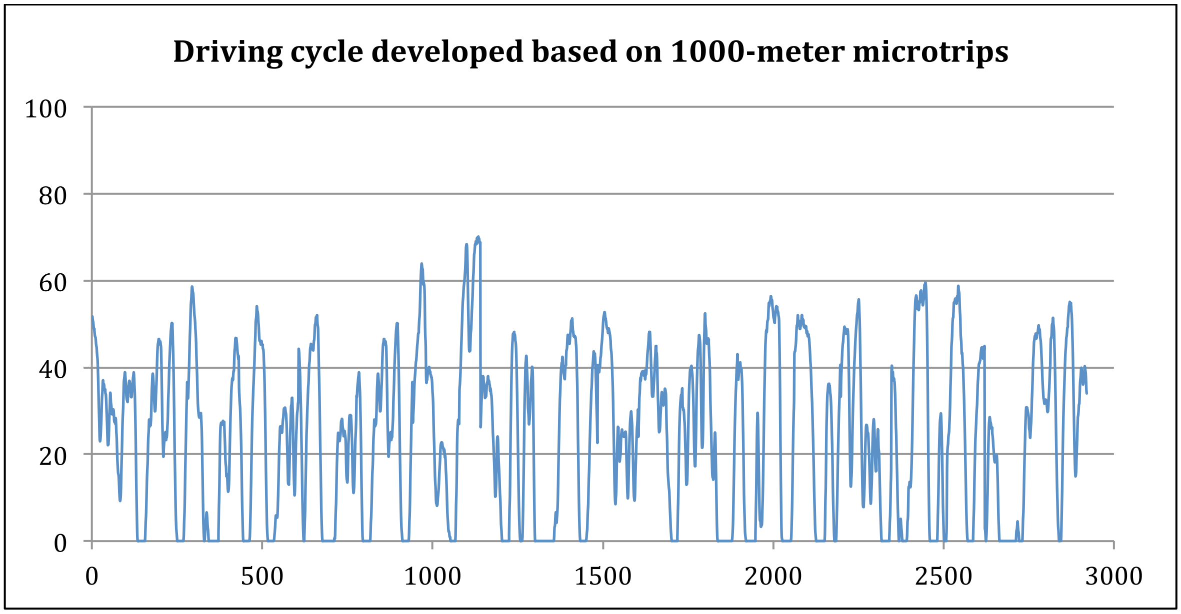

Figure C.14: The developed driving cycle based on 1000-meter microtrips

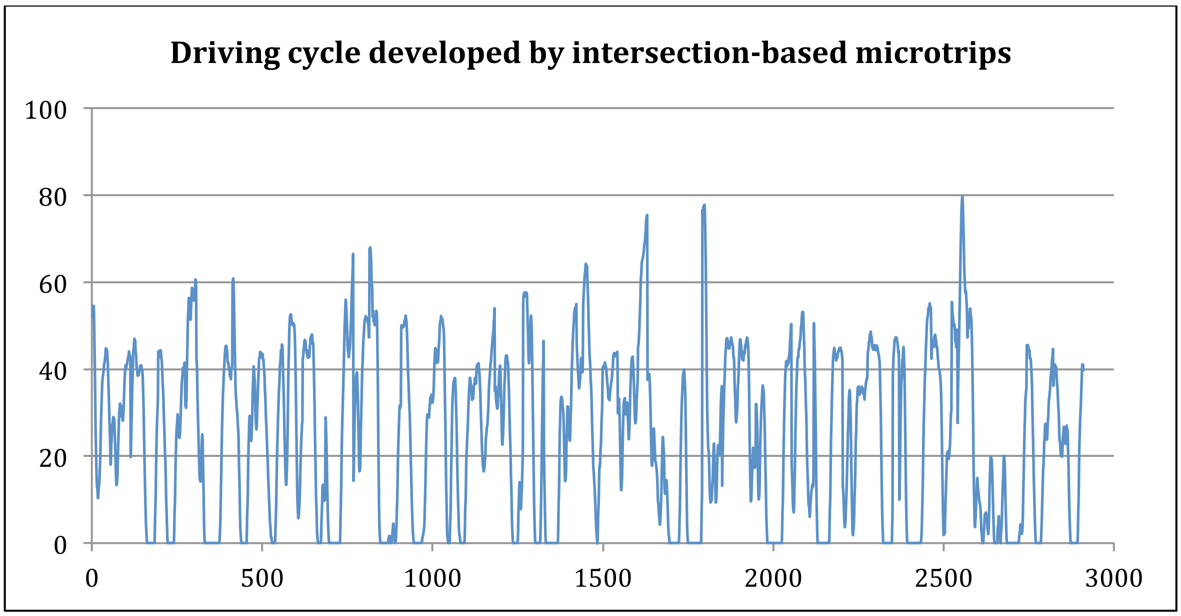

Figure C.15: The developed driving cycle based on intersection-based microtrips

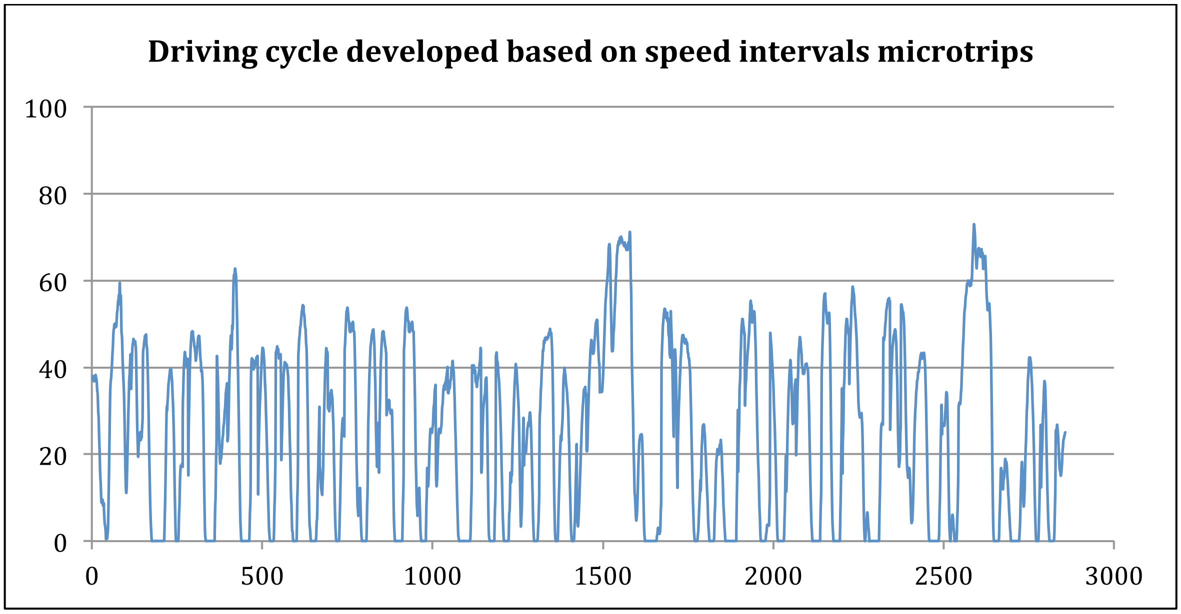

Figure C.16: The developed driving cycle based on speed intervals microtrips

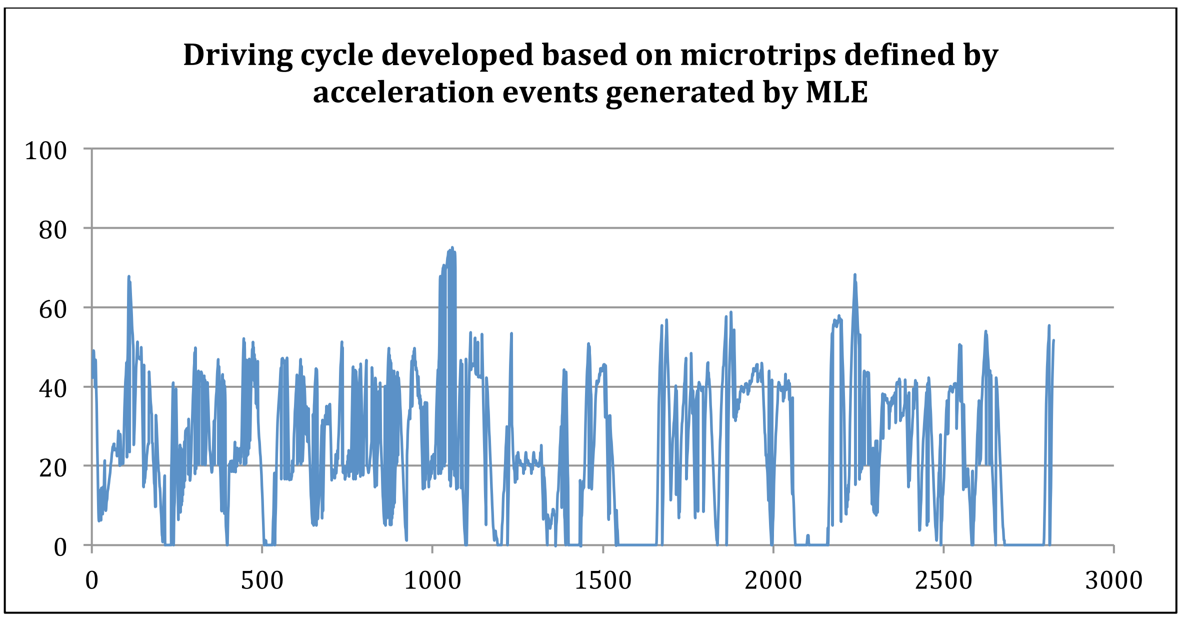

Figure C.17: The developed driving cycle based on microtrips defined by acceleration events by Maximum Likelihood Estimation (MLE)

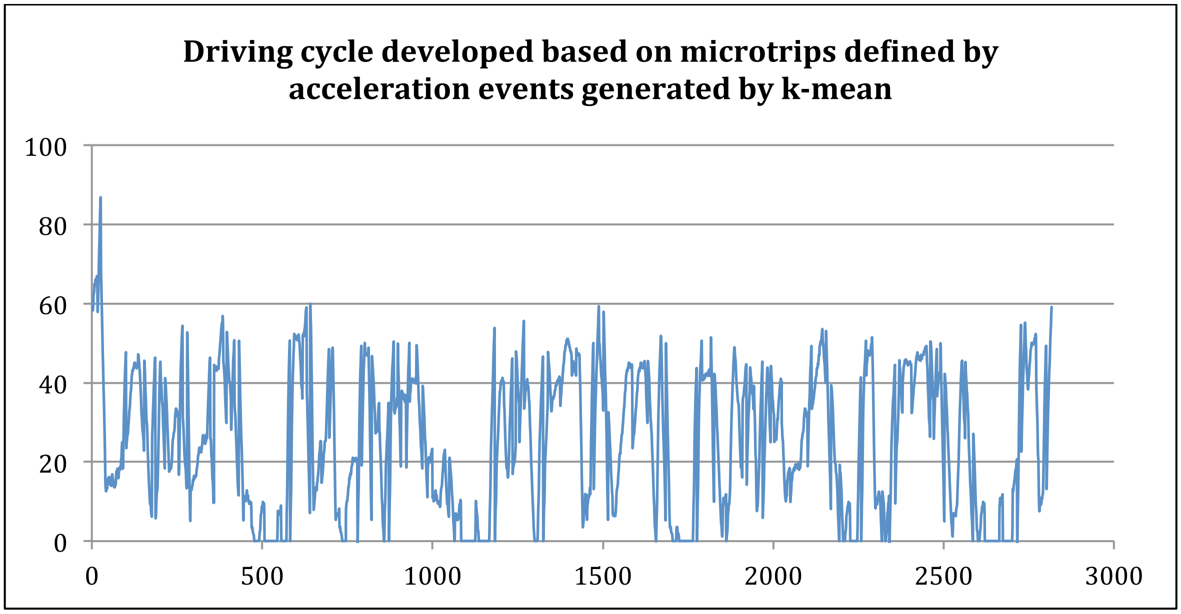

Figure C.18: The developed driving cycle based on microtrips defined by acceleration events generated by k-mean method

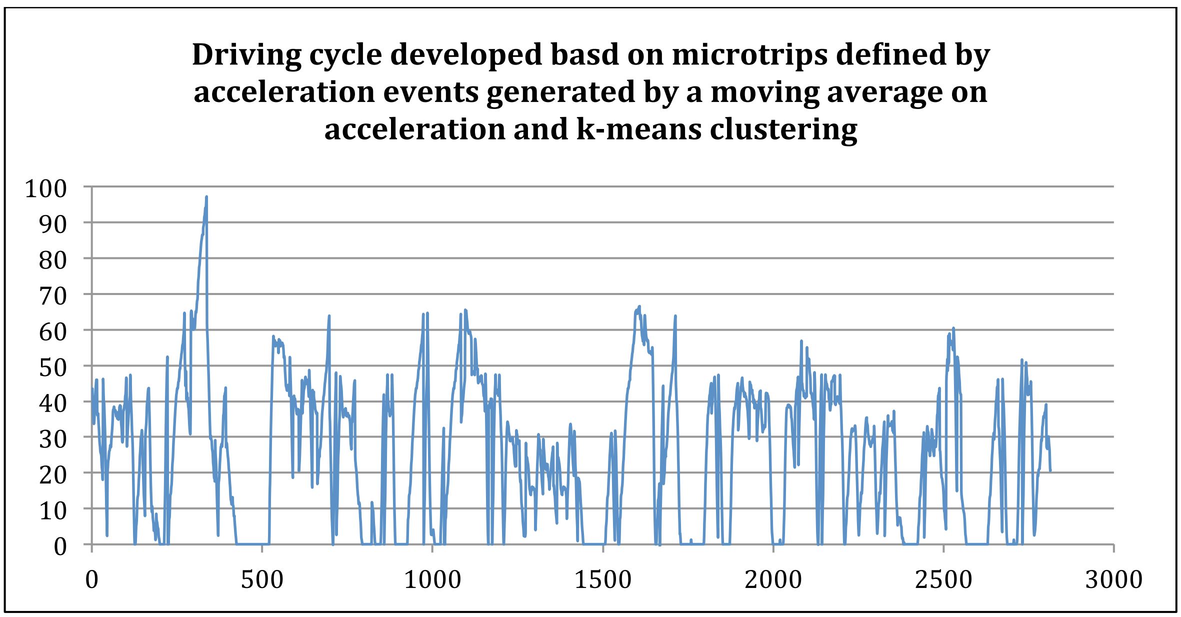

Figure C.19: The developed driving cycle based on acceleration events defined by k-means method on average moving acceleration